LEARNER MODELING USING LEARNER CHARACTERISTICS FOR IMPLEMENTATION OF ADAPTABILITY AND PERSONALIZATION IN INTELLIGENT TUTORING SYSTEM

A thesis submitted to the
University of Petroleum and Energy Studies

For the Award of
Doctor of Philosophy
in
Computer Science and Engineering

By
Amit Kumar

June 2019

SUPERVISOR

Dr. (Prof.) Neelu Jyothi Ahuja

UPES
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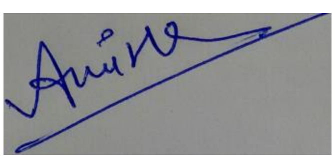
DEDICATION

This thesis work is dedicated to my late mother, Rajesh Devi, and my father, Rajendra Kumar, and my family, who has always blessed me and give guidance to raise up in the phases of life. Also dedicated to my sweetest daughter Aradhya, and my wife Sangeeta.

AUGUST 2020

DECLARATION

I declare that the thesis entitled **"Learner Modeling using Learner Characteristics for Implementation of Adaptability and Personalization in Intelligent Tutoring System"** has been prepared by me under the guidance of **Dr. Neelu Jyothi Ahuja,** Professor of Computer Science and Engineering, School of Computer Science, University of Petroleum and Energy Studies. No part of this thesis has formed the basis for the award of any degree or fellowship previously.



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CERTIFICATE

I certify that, **Amit Kumar (SAP ID - 500066317)** has prepared his thesis entitled **"Learner Modeling using Learner Characteristics for Implementation of Adaptability and Personalization in Intelligent Tutoring System"**, for the award of Ph.D. degree of the University of Petroleum and Energy Studies, under my guidance. He has carried out the work at the Department of Computer Science and Engineering, University of Petroleum & Energy Studies (UPES).

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ABSTRACT

Traditional teaching and learning largely face to face, has undergone several transformations in yesteryears with computer-based education taking over. At their initial advent, computers were used as supplementing tools to education delivery and now have progressed to the extent of offering, monitoring and controlling the learning process. While technology intervention and progress have been at upswing, teaching using computers has been largely limited to offering education to learner, without considering their individual needs and preferences. The existing tutoring systems or learning systems focus only on gathering, organizing and delivering content to the learners. They typically do not strive to understand the individual differences of a learner. However, each learner is different and has different learner characteristics, such as previous knowledge, learning style, cognitive, and meta-cognitive skills. Recently, the 'learning style' characteristics of learner have gained attention and the focus towards their impact on learning has increased. These investigations encourage educational researchers to offer appropriate tutoring strategies that best suit the learner, in order to make learning effective and aligned towards attaining the learning outcomes. The present work is focused to provide adaptivity and personalization in tutoring system by incorporating the learner characteristics, learning style and knowledge level of the learner.

The aim of the present work is to develop architecture of an adaptive intelligent tutoring system, through learner modeling that offers personalized tutoring for the domain of Seismic Data Interpretation (SDI). In current work, a novel I^2A^2 learning style model is proposed, which helps to identify the initial learning style of learner. Learner model incorporated learning style is designed, implemented and evaluated through 53 learners that include undergraduate students, educators and industry professionals of different fields. The framework of developed, prototype system, "SeisTutor" comprises of multiple fuzzy logic approaches and generic rules designed to classify the learner under different groups for providing the appropriate tutoring material. In order to provide adaptivity and personalization, the study proposed a blended approach that is a combination of the

stereotypes and fuzzy modeling approach of learner modeling by considering the learner characteristics such as prior domain knowledge level and the learning style. The adaptive learner model is developed under the three submodules: Learner Characteristics Module, Learner Classification Module, and Learner Adaptation Module. This learner modeling approach allows the system to adapt the learning content to learner through selection of appropriate tutoring strategies. This novel approach has the advantage to reduce the learning time and provide effective learning.

The learner model represents knowledge of the learner using a stereotype model. Fuzzy modeling technique has been used to provide adaptive and personalized instructions to the learners. To evaluate the efficacy of the learner model, two levels of evaluation, comprising the evaluation of learning performance and evaluation of learner's perceptions has been used. To evaluate learning performance, ANOVA statistical test has been conducted on scores of participants in pre-tutoring and post-tutoring tests, which is a well-known method for assessing the effectiveness of a training program. The computed value of F-ratio of ANOVA test, $F_{calc} = 327.22$ at $\alpha=0.05$, where α is significant level, and the tabulated value of the F-ratio of ANOVA test, $F_{\alpha} = 243.3$ (as per F-Table). Here $F_{calc} > F_{\alpha}$, hence the alternate hypothesis H_a: $\mu_1 < \mu_2$ is accepted and null hypothesis H_o is not accepted. This indicates significant difference in achievement of learner outcomes, quantified by learning gain of 42.26%. To evaluate the learner's perceptions, learner feedback questionnaire has been used and it is divided into five pre-identified parameters, as per responses of learners in learner feedback questionnaire. The pre-identified parameters are: System Effectiveness, Adaptability, Personalization, System Support, and Ease-of-use also known as system performance parameters. The results shows that system effectiveness is 84.36%, adaptability is 85.29%, personalization is 83.22%, system support is 82.45%, and ease-of-use is 86.23% out of 100. The results of the evaluation were encouraging and significant improvement has been recorded, because SeisTutor has appropriately judged the learning style of learner and provided a personalized content presentation to them. The results show that, personalizing and adapting to the learner needs and preferences has a positive impact on performance.

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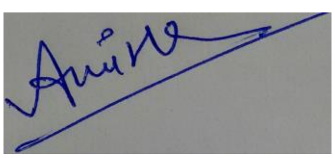

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
LS	Learning Style
DKT	Domain Knowledge Test
LL	Learner level
TS	Tutoring Strategy
LST	Learning Style Test
ML	Machine Learning
FL	Fuzzy Logic
IMG	Imagistic
INT	Intuitive
ACO	Acoustic
ACT	Active
BEG	Beginner
INT	Intermediate
EXP	Expert
LP	Learner Profile
LM	Learner Model
CM	Content Model
DM	Domain Model
TM	Tutoring Model
ITS	Intelligent Tutoring System
AITS	Adaptive Intelligent Tutoring System
LSQP	Learning Style Question Pool
LSD	Learning Style Dimensions
RPS	Recommended Pedagogy Style
QM	Quiz Model
DKOM	Domain Knowledge Object Model
DKDM	Domain Knowledge Database Model

CTS	Course Tree Structure
CDG	Course Dependency Graph
W	Week
L	Lesson
T	Topic
Trimf	Triangular Membership Function
IS	Increasing Section
DS	Decreasing Section
DoE	Degree of Engagement
CR	Correct Response
HT	Hint Taken
TT	Time Taken
LP	Learner Performance
SDI	Seismic Data Interpretation
SE	Standard Error

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

In this chapter introduction, problem statement, need and motivation, research questions and scope of the research have been described. Subsequently, the objectives of research, methodology, contribution, and organization of the thesis have been presented.

1.1 INTRODUCTION

Intelligent Tutoring System (ITS) is an advanced generation educational software incorporating artificial intelligence techniques or mechanisms, involving minimal intervention of human teacher (Hatzilygeroudis, I., & Prentzas, J. 2004). ITS refers to the computer based instructional system that provides personalized learning to learner by adapting learning contents and their presentation as per needs and preferences of the learner for its design and implementation's. ITS combines several disciplines of study, such as, computer science, learning science, artificial intelligence and psychology (Nwana, 1990; Graesser et al., 2012) is presented in Figure - 1.1.

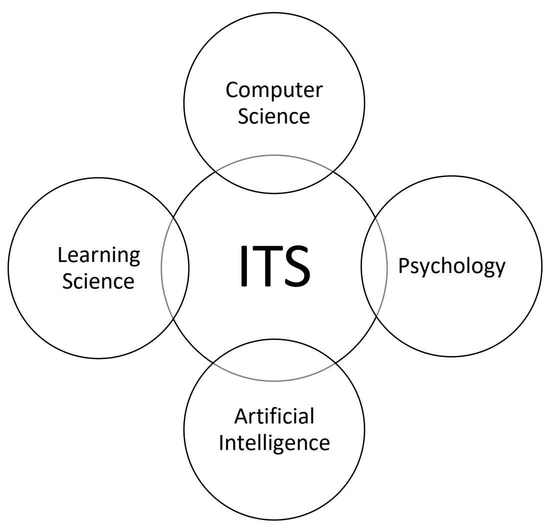


Figure 1.1 - ITS Discipline

Computer Science characterizes the method, and technology utilized by the tutoring system/e-learning system in the learning framework. *Psychology* addresses, how the learner think and learn. It represents the cognitive and meta-cognitive characteristics of learner while interacting with the ITS. *Artificial Intelligence (AI)* addresses the intelligence methods/techniques in the development of ITS. *Learning Science* addresses, how to provide the best learning/teaching supports is an interdisciplinary domain and develops the cognitive-psychological foundation of human learning.

Although many Intelligent Tutoring Systems/E-learning exists in literature and each have different architecture (Wang & Mitrovic, 2002; Conati et al, 2002; Wenger, 1986; Chou et al, 2003; Zapata-Rivera et al, 2004; Baffes & Mooney, 1996). A typical architecture of ITS comprises of four main components: Learner Model, Tutoring Model, Domain/Knowledge Model and Learner Interface Model. The following Figure 1.2 represents the basic architectural model of ITS.

1. *Learner model* stores the data about the learner's such as prior knowledge's, errors, misconceptions, learning style, preferences, cognitive and meta-cognitive abilities (Freedman et al., 2000). This model records the activities of individual learner during learning (e.g. competency level, learning style, time spent on topics and quizzes, correct responses, hint taken etc.) and track how well the learner performs on the learning materials which is being taught (Massey et al., 1988).

2. *Domain model* or content model stores the learning material/content, which is to be taught to the learner and is considered as a source of knowledge (Woolf, 2008). This model contains the expert knowledge that the tutoring system used to teach to the learner such as lessons, topic definitions, exercises, assignments, etc.

3. *Tutoring model* makes the decision about instructional strategies, actions performed by learner, information provided by learner model and domain model. This model contains the actual teaching process or pedagogy. This model takes the data from the learner model and generate appropriate pedagogy according to the needs and preferences of different learners (Beck, J.E. & Chang, K.M. (2007).

4. *Learner interface model* is known as the communication model that allows learner/teacher interaction with the tutoring system. This model provides different methods of communication concerning the learner/teacher and the intelligent tutoring system. There are different method have been used for interaction such as Graphical User Interface (GUI), dialog box, and different screen layout.

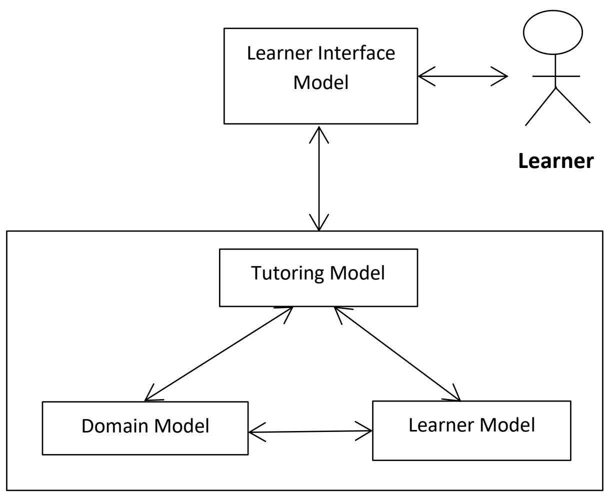


Figure 1.2 - ITS Architecture

As the evolution of the internet, teaching through digital media has gained speed since it offers the learning material as per their convenience (Chrysafiadi, K., & Virvou, M., 2013). The web-based educational systems overcome various dependencies (e.g. learning preference, location dependency, time constraint, lifelong learning, on-demand learning, collaborative support, presentations, and feedback) caused by the traditional classroom teaching (Xu, Wang, & Su, 2002). Numerous ITS has been implemented successfully in the tutoring of various subjects/domains such as Electrodynamics, Natural language, Physics, English Grammar, SQL Tutor, C++ Tutor, Physiology for Medical Students, and database (Virvou, M., & Kabassi, K., 2002; Evens et al, 2001; Gertner, A. S., & VanLehn, K.,2000; Vicari et. al., 2008; Wang & Mitrovic, 2002; Mitrovic, 2003; Baffes & Mooney, 1996; Khuwaja et. al., 1994; Naser, S. S. A., 2008; Chien et al., 2008). Therefore, no such tutoring system is exist for teaching the Seismic Data Interpretation (SDI).

In the current work, we have implemented an adaptive intelligent tutoring system christened *'SeisTutor'* for teaching SDI. The *'SeisTutor'* is an endeavor to address to teach the essential seismic interpretation skills and fundamentals of this field have been gathered, to form the subject matter. This knowledge, initially in tacit form, has been transformed to explicit form and further to tutor-able form. As each learner may have a different competency level and learning pattern, '*SeisTutor'* has been developed, to initially interrogate, to adjudge the learner sufficiently, to offer learning through an exclusively designed learning plan, being referred to here as *'tutoring strategy'*. Further, it also assesses the learner as per his/her performance during the tutoring sessions.

In this work, we will mainly focused for design and develop an adaptive learner model, which is an essential component of AITS. The adaptability and personalization features of the system are heavily dependent on the learner model (Chrysafiadi, K., & Virvou, M., 2012). The learner model is implemented using a fuzzy logic technique which is a soft computing technique of Artificial Intelligence (AI). The fuzzy logic technique is used because it mimics the behavior of learner and provides the human-like instructions to the learner. The fuzzy logic technique provides the 'Intelligence' features in the tutoring system. 'Intelligence' features enable tutoring systems to understand the learner's behavior, cognitive, and meta-cognitive skills. The fuzzy logic technique is the rule-based inference system to guide the actual learning path in the tutoring system to make it personalized and adaptive.

1.2 PROBLEM STATEMENT

The e-learning modes of education are increasing day by day and provide education without considering learners individual needs and preferences. Understanding individual differences and needs of learning are important issues not sufficiently addressed in the current educational system. Particularly, the tutoring system is faced with the challenge to provide adaptation and personalization by considering the learner needs, preferences, knowledge level, cognitive skills, and other characteristics. Therefore, adaptability is an important issue and a challenge for learning systems, due to individual diversities and changing learner requirements (Lo, Chan, & Yeh, 2012). Therefore, a learner modeling technique is introduced in ITS development aiming at personalization and adaptation.

The learner model is the most significant component in the ITS targeted to provide the adaptation and personalization. The aim of current research is to answer 3 basic questions on learner modeling - *'What, Why, and How to model?'*

Hence the problem statement is:

"Learner modeling using learner characteristics for implementation of adaptability and personalization in intelligent tutoring system"

1.3 NEED AND MOTIVATION

There have been quick advancement in the conveyance of web instruction with the development and progression of web innovation. However, online learning manages the differing foundations and heterogeneous needs of learners. According to Graf & Kinshuk (2010), learner's individual interests play a key role in web-based learning conditions. This famous technique for e-learning isn't just about conveying web content to an imminent learner, yet additionally takes into account the requirements of teachers, and furthermore to learners, who need to build up their own repository of subjects. E-learning gives training to various learners and is advantageous for learning to any period of time and place, without knowing their learning priorities, needs, aptitudes, and competency levels. Every individual is unique, which is the reason the learning procedure followed by every individual is altogether different from that of the other individual.

As there are various types of students, they have distinctive and unique learning attributes that influence their learning procedure and positively decide their learning inclinations, needs, and levels of learning. A few investigations have been led around these distinctions for improving the learning adequacy during the instructing and learning condition (Bozkurt and Aydogdu, 2009; Demirtas and Demirkan, 2003). Numerous instructive hypotheses and studies guarantee that the learning procedure can be improved, given the student attributes are distinguished.

In face-to-face (classroom) teaching, the teacher cautiously makes efforts towards adapting to the learning competencies and styles of learners. Traditional web-based e-learning/ITS system suffers from shortcomings, like lack of flexibility, adaptability, personalization, learner’s collaborative support to the system (Xu, Wang, and Su, 2002). According to Schiaffino, Garcia, & Amandi (2008), adaptability in web-based tutoring systems has been an active research interest for researchers for improving the learning process. So, there a need to identify the learner attributes that may improve the learning processes and can offer adaptation to every individuals.

According to Lee & Park (2008), adaptivity is significant in learning procedure to give and oversee learning course adjusted for every user, observing and deciphering user exercises according to their requirements and learning inclinations. The versatile element of the e-learning system coordinates the exercises and maps the learner's interest in learning material. As per Felder and Silverman (1988), numerous scientists accept that mentoring can be compelling and powerful by planning the learning material with the student's inclinations and their learning styles. It has been recognized as a solid connection between learning style and versatile mentoring framework. Various students have distinctive methods of learning, and every student wants to learn in his/her own individual way that best suits according to a person's qualities, for example, student past information, learning style, psychological and scholarly capacity, or backgrounds. Mentoring according to these individual attributes of a student, makes learning compelling and advances the utilization of a versatile tutoring framework for improving the learning. To improve the execution of learning, the instructor ought to foresee which learning style is generally adjusted to the student.

It is a challenging to design an adaptive tutoring system that meets all requirements of learner in light of the fact that every learner has different needs as well as their individual learning characteristics (Lo, Chan, and Yeh, 2012). The individual characteristics are referred as learner ‘attributes’ or ‘object’. Therefore, it is essential to inspect each and various learner characteristics that can provide adaptivity in different learning conditions (Brusilovsky and Millan, 2007). This could be the option to check its significance for future research in context to improve the learning procedure. According to many studies (Tseng, Chu, Hwang, & Tsai (2008), Graf, Kinshuk & Liu (2010)) uncover that, adaptive tutoring system based on learning style characteristics are more productive, increment student satisfaction level, limit learning time, and improve learning accomplishment. In this way, learning style is one of the critical characteristics to concentrate on singular contrasts while building up a adaptive tutoring framework. (Graf, Liu and Kinshuk, 2009; Liegle and Janicki, 2006).

So, it is important to focus on the learner model, which is one of the key component of adaptive tutoring system that represent numerous learner characteristics such as competency level, preferences and learning style (Brusilovsky and Millan, 2007). According to Jeremic, Jovanovic, and Gasevic, (2012), learner modeling can be characterized as the way toward gathering the learner significant information so as to deduce the current intellectual condition of learner and to speak to it in order to be available and valuable to the ITS for offering adaptation. For building adaptive learner model, it must be viewed as that, what are the basics learner characteristics, and how to demonstrate them to guarantee the framework forward-thinking.

The learner characteristics utilized in the learner model incorporate learning style and inclinations, competency level, psychological viewpoints, and meta-intellectual angles. As indicated by Hung, Chang, and Lin (2015), a mixed learning styles model can be useful in building up the adaptive framework. The learner model could be initialized using the static characteristics of the learner. According to Denaux, Dimitrova, and Aroyo (2005), the initialization of the learner model referred to as a 'cold-start-problem' and can be understood by the grouping of learner. In this strategy, a group is assigned to the learner depends on his/her predefined characteristics and this empowers the framework to begin rapidly to provide customized instruction to that group.

Therefore, the improvement in the learner model is the key factor for planning an adaptive mentoring framework. Learner modeling is utilized for the advancement of an adaptive learner model and the key factor that influences the instructional choice (Li et. al., 2011). Learner modeling has experienced utilizing the various demonstrating strategies, for example, Overlay Model, Machine Learning Technique, Stereotype Model, Bayesian Networks Modeling, Constraint-Based Modeling, Perturbation Model, Fuzzy Learner Modeling, Ontology Modeling Techniques and Cognitive Theories. The research challenge in the scope of current work is the learner modeling, so as to give adaptability and personalization in Intelligent Tutoring System.

Need: Design and Develop an effective Learner Model for adaptability and personalization in Intelligent Tutoring System.

1.4 RESEARCH QUESTIONS

This research aim is to provide adaptability and personalization in intelligent tutoring system through learner modeling using the learner characteristics. For the same, investigation has been carried out and the following research questions have been framed.

- What data and information about a learner should be gathered to make learning effective?
- What are the learner characteristics that we want to model?

- How can the learner systems be made adaptable, so as to deliver personalized and learner-centric learning?
- What are the significant attributes of a learner that is utilized in the learner model to make the framework adaptable?
- What are the learner modeling techniques?
- Which approaches of learner modeling are to be utilized to model the learner in order to keep the system up-to-date?
- How to assess the accuracy of learner model?
- How to evaluate adaptability and personalization of the learner model?
- How to assess the effectiveness of the system?

1.5 SCOPE OF RESEARCH

Currently, individualization of e- learning has gained speed. For this reason, there are many parallel studies focusing on web based learning, to make system adaptable to learner needs and preferences. To make system adaptable, it is necessary to concentrate on the learner modeling in e-learning condition Therefore, the research area of learner modeling has matured in yesteryears and offers promise to be harnessed for incorporation of adaptation and personalization in ITS.

The focal point of present work is, structure and advancement of a adaptable learner model (utilizing learner characteristics) for adaptability and personalization in ITS (Figure 1.3).

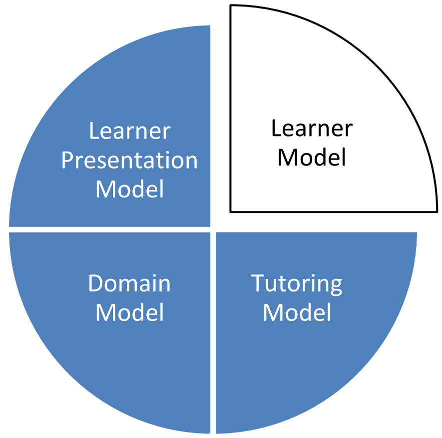


Figure 1.3 – ITS Model

1.6 OBJECTIVE OF RESEARCH

"Learner modeling using learner characteristics for implementation of adaptability and personalization in intelligent tutoring system"

The sub objectives of the research are

1. To investigate literature of ITS with emphasis on adaptability and personalization.
2. To design learner model using identified learner characteristics.
3. To develop an adaptable ITS model using learner modeling.
4. To assess adaptability through evaluation of developed ITS.

1.7 CONTRIBUTION TO THE RESEARCH

Novel I^2A^2 Learning Style Model

One of the objectives of present work is the development an adaptive ITS through the implementation of an adaptive learner model using learner characteristics. The learning styles of learners should be known first to provide the adaptation in ITS. In this way, a learner-modeling approach using learner characteristics should be developed for distinguishing the behavior and the learner actions. In order to provide adaptivity, a novel I^2A^2 learning style model is developed, which includes four learning dimensions i.e. Imagistic, Intuitive, Acoustic, and Active.

Adaptivity can be provided in ITS if the learning styles of learners are identified. Considering the learner characteristics i.e. learning style, an idea to offer adaptive learning content in ITS was originated. This concept has been implemented in ITS, christened 'SeisTutor', and has been presented in this research work. The assessment showed that learners, who were taught a course in a manner that matches their learning styles, learn effectively and in a shorter length of time. The proposed learner style model has been designed, implemented, and evaluated with 'SeisTutor'.

Fuzzy Inference approach for implementation of the learner model using learning style

This research presents design of the system for implementing adaptive learner model along with features such as adaptive tutoring strategy, assessment of learner performance and degree of engagement. These features hold the potential to encourage learner and build in positive attitude towards learning.

The learner model has been developed using stereotype modeling technique of learner modelling, which has been implemented by fuzzy inference soft computing technique. A fuzzy membership function was created with linguistic variables, fuzzy sets and fuzzy rules. Fuzzy rules are adapted from human way of thinking according to the principle of fuzzy logic. The fuzzy model is similar to a human thinking process and responsible for a good judgment. This permits the covering of obscure ideas and overthrows the limitations such as lack of learning style and learner data. Moreover, the proposed approach has distinctive configurable fuzzy rules.

Adaptive and Personalized Tutoring Strategy

A new framework of selecting the tutoring strategy has been developed in this research. The framework has a tutoring strategy model to offer an appropriate tutoring strategy (personalized) to learners. The tutoring strategy comprises of lessons and quizzes which is based on several learning attributes. These learning attributes incorporate educational parameters such as learning style, correct responses, hints, and competency level (see Section 5). The learner has been offered a greater degree of flexibility, in terms of providing tutoring as per the learner's preferences and comfort. Further, there is a provision to alter tutoring strategy during ongoing tutoring as well. This is controlled through the fuzzy rules. The fuzzy rules are configurable by the teacher.

The tutoring strategy framework has an advantage that it takes meta-strategy for learning contents and then generates the best-suited tutoring strategy according to the given learning condition. The meta-strategies are based on the learner characteristics such as learning styles of learner and the competency level learner. This has the benefits of taking into consideration, the configuration of all parts of the tutoring strategies are according to his/her learning style and the degree level of learning content (Beginner, Intermediate, and Expert). Additionally, the system presents the idea of revisions of lessons, and to change the tutoring strategy based on his/her choice as per comfort. Moreover, the system supports is largely learner-centric and based on learner performance, competency level, and their learning style. Additionally, the advantage over existing ITS is to offering more practical help to learners in the learning environment.

SeisTutor: A Seismic Tutor

An adaptive intelligent tutoring system christened '*SeisTutor'* for the domain of Seismic Data Interpretation (SDI) has been developed in this research work. Over several years' seismic data as seismic snaps/images has been interpreted, to yield reasonably acceptable inferences about subsurface geology. As there are no formal interpretation rules, the interpretation knowledge is largely tacit in nature, predominantly dependent on interpretive powers, capabilities and experience of human experts, the seismologists. Novice seismologists, expected to deliver near accurate interpretations, face initial difficulties and rarely have time, either to go through long training cycles or wait to gain enough field experience naturally with passing time.

SeisTutor is an attempt to address this problem through learner modeling. As each learner may have a different competency level and learning pattern, SeisTutor has been developed, to initially interrogate, to adjudge the learner sufficiently, to offer learning through an exclusively designed learning plan, being referred to here as 'tutoring strategy'. Further, it also assesses the learner as per his or her performance during the tutoring sessions. While SeisTutor does not guaranty, complete mastery on the subject matter, it is a modest effort in the direction of making not only the knowledge on this rare domain available in tutorable form, but also as offered in a learner-centric form as per individual learner preferences.

Development of Inventories

Learning Style Question Pool (LSQP) and Learner Feedback Questionnaire (LFQ), the underpinning of these inquires/tools, formulate assessment of learners learning style and perception on the developed system.

1.8 STRUCTURE OF THESIS

The complete thesis is structured in the following eight chapters.

Chapter 2 details the background and literature review on intelligent tutoring systems/e-learning system and learner modeling approaches, followed by a description of common learner characteristics along with their comparative analysis and use in the ITS. In addition to a review of published literature on learning styles and definitions, their summary of available learning style models, their criticisms, challenges, and limitations has been presented.

Section 3 portrays the structure of the proposed learner model along with its sub-components, for example, learner characteristics model, learner classification model, and learner adaptation model. The fuzzy logic techniques are described for implementation of all sun-modules of learner model. Subsequently, the design of the tutoring model along with sub-modules has been described.

Chapter 4 details the proposed novel I^2A^2 learning style model and various learning style dimensions. Subsequently, the summary of learning style dimensions along with the recommendation of the proposed model for education has been discussed.

Chapter 5 describes the overall architecture of prototype developed - SeisTutor, which comprising the learner presentation model, domain/knowledge model, tutoring model, adaptation model, and learner model with their submodules.

Section 6 depicts the plan and implementation of developed prototype - SeisTutor. The Data Flow Diagram (DFD) and the screenshot of the component of SeisTutor is shown

Chapter 7 details the evaluation of learner performance and the developed prototype – SeisTutor. The results and findings of the evaluations are discussed. The results of the pre-tutoring tests, the post-tutoring tests in terms of learning gain is discussed. The SeisTutor is evaluated through learner feedback questionnaire and learner's reaction has been recorded to analyze the effectiveness of system using performance parameter.

Chapter 8 covers the summary of research contributions, conclusions of thesis, along with recommendations and future scope.

CHAPTER 2: LITERATURE REVIEW

This chapter presents the writing survey identified with this exploration work. Also, this chapter presents the findings to the field of ITS focused on the learning style of learner. The related work is focused around the current E-learning/ Intelligent Tutoring Systems with the subject area for which it is used in the e-learning environments, learner modeling, learning modeling approaches, and learner characteristics. In addition to that, the role of learning styles in the E-learning/ITS along with the literature on learning style models are discussed.

2.1 BACKGROUND

There has been persistent research in the field of ITS in recent years with some eminent successes and ITSs have given a remarkable advantage to learners from various learning domains (Chien et al., 2008; Naser, S. S. A., 2008). A lot of educationalist/researchers have been explored ITS with focused on providing personalized and adaptive tutoring to the learners. The objective of the ITSs is to deliver the adaptive content that best suits the learner needs and preferences. ITSs have contributed to improving the learning outcomes, even for the difficult subject such as mathematics when we compared to the traditional classroom teaching (Feng, M., et. al., 2008).

This section introduces some of the intelligent tutoring system exist in the literature for different domain.

TANGOW [19] (Task-based Adaptive learNer Guidance On the Web) is a learning framework intended for building online courses on the premise of tutoring techniques. For adaptivity, TANGOW fuses two measurements of Felder model, in particular, the

Sensing/Intuitive and the sequential/global measurements. For learner modeling, the mixed approach was used and the learner asked to attempt the Felder learning style questionnaire when learner login the first time. Subsequent, after initialization of the learner model, it is naturally refreshed by watching the students' activities in the course.

CS383 [22], is a computerized educational framework that used the Felder model of learning style to provide the adaptivity. Felder learning style parameters were used to embed the adaptivity in the tutoring system: sensory/intuition, visual/verbal and sequential/global. This framework compels learner to settle on decisions and in this manner effectively include them in the learning procedure, which encourages dynamic learning.

INSPIRE [4] (Intelligent System for Personalized Instruction in a Remote Environment) tutoring system provides learners a chance to choose their learning objective and in like manner creates learning materials and exercises according to the learner's knowledge levels, preferences, and learning style. The learner has authorized to customize the instructional strategy and make changes to learner model. The adaptivity is provided based on the dimension of the Honey and Mumford, the learning contents are adapted based on the different presentation methods and learner could update the learner model.

F-SMILE [3] is an agent-based computerized learning system that assists the novice learner to modify the content or data stored in the learner computer on which he/she is working. It provides an adaptive framework to the learner through an adaptation of learning content, based on learner modeling. F-SMILE has multi-agent that communicates to the learner to solve the problem and uses four main agents: learner, advisor, tutor, and speech-driven agent

ICICLE [5] is an adaptive tutoring system for the deaf learners for the domain of English grammar. ICICLE use the overlay and stereotypes model for learner modeling and ICICLE learner model captures the learner’s expertise of the grammatical formulas and predicts the general adaptive grammar rule for the learner.

InfoMap is designed for the domain of ontology for system browsing and the processing of the computer system [6]-[7]. It has used an overlay model for learner modeling combine with bug model to identify the scarce knowledge of learner.

ACE [8] (Adaptive Coach for Exploration) is a learning framework for mathematical functions designed using the Bayesian Networks learner modeling techniques. It provides an intelligent learning path through exploration of learning difficulty levels and assess the learner needs to guide to provide the adaptive learning material.

Andes [9] is a tutoring framework for the diagnosis of the Newtonians Physics concept of learner and learner modeling is performed by the Constraints Based Modeling techniques.

VIRGE [10] is based on the cognitive theories and allows the learner to captures his/her emotional state and used by the [11]. It adopted the theory of OCC to provide the evidence of learner while they learn.

AMPLIA [12] is a tutoring framework used to train the medical students and a hybrid learner modeling techniques were used which provide a development support of diagnostics reasoning of disease.

E-Teacher [13] is used to automatically detect the learning style of the learner from learning behavior. Learner modeling is performed through the Bayesian Networks modeling approach and designed to learner object-oriented concept and UML diagrams.

ADAPTAPlan [14] tutoring framework used machine learning and fuzzy logic modeling to evaluate and assess the learning activities and assignments.

AUTO-COLLEAGUE [15] is an adaptive learning system for the UML class diagrams and used a hybrid learning modeling techniques using the perturbation and stereotypes modeling techniques. This system is based on the learner performance level and the learning actions [16].

KERMIT [17] teaches the database system and learner model is designed using the overlay model and constraint-based modeling techniques. It tracks the learner actions during learning and adapts the behavior to provide the adaptive concept of SQL design.

WILEDS [18] is a web-based tutoring framework based on the overlay learner modeling to teach the digital system.

The following section discusses the concept of learner modeling, including various modeling techniques and learner characteristic, also discuss the important learner characteristics that help to provide the adaptive content.

2.2 LEARNER MODELING AND APPROACHES

According to Jeremic, Jovanovic, and Gasevic, (2012), learner modeling can be characterized as the way toward gathering the learner significant information so as to deduce the current intellectual condition of learner and to speak to it in order to be available and valuable to the ITS for offering adaptation. For building adaptive learner model, it must be viewed as that, what are the basics learner characteristics, and how to demonstrate them to guarantee the framework forward-thinking. The learner characteristics utilized in the learner model incorporate learning style and inclinations, competency level, psychological viewpoints, and meta-intellectual angles.

As indicated by Hung, Chang, and Lin (2015), a mixed learning styles model can be useful in building up the adaptive framework. The learner model could be initialized using the static characteristics of the learner. According to Denaux, Dimitrova, and Aroyo (2005), the initialization of the learner model referred to as a ‘cold-start-problem’ and can be understood by the grouping of learner. In this strategy, a group is assigned to the learner depends on his/her predefined characteristics and this empowers the framework to begin rapidly to provide customized instruction to that group.

There are many learner modeling approach/techniques are available in the literature which has been critically examined and discussed in this section.

2.2.1 Overlay Approach

This is the most mainstream approach utilized in the learner modeling and has been used by several systems considering that the learner may have incomplete but correct domain knowledge. According to Martins, Faria, and Vaz de Carvalho (2008), learner model is the subset of domain model, which gives the master level of information about the learning contents. According to Nguyen and Do (2008), there is an associated connection between the learner model and the domain model. In the MEDEA, Overlay Modeling Approach is used for learner modeling in which learner knowledge level in a particular domain is estimated (Carmona and Conejo, 2004). In addition to that ICICLE (Michaud and McCoy, 2004) used Overlay Modeling Approach that performs learner modeling with a focus on learners grammatical concepts and predicts the most appropriate grammar rules for the language.

2.2.2 Stereotypes

Stereotype is one of the most famous methodologies of learner modeling introduced in system called GRUNDY (Rich, 1979). Stereotyping characterizes the student into various gatherings dependent on his/her normal characteristics. These groups are known as stereotypes and share the common characteristics as criteria. A new learner is assigned to a stereotype as per characteristics e.g. Stereotypes model considering the learning styles characteristics of the learner. In these cases, the stereotypes could be (visual, auditory, active, reflective, sensory, and intuitive) accordingly. According to Tsiriga and Virvou

(2002), Stereotypes is particularly important in reasoning about a learner and also for initializing a learner model by considering their characteristics.

WELSA utilized generalizations for adjusting the learning substance dependent on the learning inclination of student (Popescu Badica, and Moraret, 2009). Tourtoglou and Virvou (2008) used the hybrid approach for learner modeling by combining the stereotypes and perturbation technique for UML learning. Another adaptive tutoring system used the stereotypes in CLT C++ tutor (Durrani and Durrani, 2010).

2.2.3 Machine Learning Approach

Learner modeling involves the process of inferring the learner's behavior based on his/her characteristics like earlier information, intellectual capacities, learning styles, inclinations, and inspirations. It is a challenge to predict these characteristics, the learners' action and behavior to develop an adaptive tutoring system (Webb, 1988). Training data provided by observation of user actions during ongoing tutoring system that help the learning system to predict the user future action.

Baker (2007) reports the approach of machine-learning that is used to detect the off-task behavior of the learner. In GIAS (Castillo, Gama, and Breda, 2009), machine learning technique has been used in with stereotype model for choosing the appropriate learning contents to make system adaptable. In order to implement the personalization, Al-Hmouz, Shen, Yan (2010) combines the two machine-learning approaches. Finally, machine-learning approach is used to automatically improve the learning performance and effectiveness of learner model (Li et al., 2011).

2.2.4 Cognitive Theories

In order to implement learner model, many researchers have adopted cognitive theories. The learner model is used to find out the individuality based on the cognitive skills

(Balasubramanian and Margret Anouncia, 2016), and also describe the learner behavior during learning process and use to classify learner based on their logical thinking, memory, perception, and understanding.

2.2.5 Fuzzy Learner Modeling

ITS does not provide the direct interaction between the teacher and the learner model, so it is difficult to observe and measure the learner knowledge level (Jeremic et al., 2012). During the learner diagnosis, learner actions, like selecting the appropriate course and learning contents, pose numerous challenges, leading to uncertainty in assessing the learner mental state and behavior. To handle the uncertainty of data, fuzzy logic methodology has been introduced by Zadeh (1965).

According to Xu et al. (2002) and Kavcic (2004), fuzzy logic is used to provide personalization in learning material, course test, creating the navigational flow graph and adoption in learner reasoning. The Fuzzy logic used in learner diagnosis has been further used to tailor the pedagogical decision according to learner characteristics.

2.2.6 Constraints Based Modeling

Constraints Based Modeling (CBM) offers that learners generally make errors while performing any task. Despite the fact that he/she has been educated in the right way and this based on one of the theories ‘learn from mistakes’ (Ohlsson’s, 1994). It depends on the condition for example pertinence, a condition that must be valid before an imperative is pertinent to the current arrangement and fulfillment. According to Ohlsson & Mitrovic (2006), this approach is potentially sound for the intractable problem of learner modeling. Therefore, the main advantage of CBM is that its computation is very simple, does not need an expert running module and does not require extensive studies of learner bugs.

According to Holland, MItrovic, & Martin (2009), Constraint based approach used by J-LATTE intelligent tutoring system for java programming language. INCOM also an ITS, uses the CBM approach for recognizing learners error and misconceptions (Le et. al., 2009).

2.2.7 Perturbation

This technique represent the learner misconception and erroneous competency level. This model focuses on mistakes done by learner and is useful for the learner diagnosis and reasoning. The mistakes in this model are usually known as bugs and errors. These blunders are fabricated either by empirical investigation of missteps or by producing botches from the misguided judgments (Chrysafiadi and Virvou, 2012). In the past decade, many personalized systems embedded the perturbation learner model for predicting the learner behavior. InfoMap (Lu et al., 2005) involved thirty one types of addition errors and fifty one types of subtraction error. Additionally, LeCo-EAD (Faraco et al, 2004) also used perturbation model to reasoning the correct and incorrect knowledge prepositions.

2.2.8 Bayesian Networks

Another important approach to handle the uncertainty of data in learner modeling is Bayesian networks. It is a directed graph in which nodes represent the parameter or variable, and the edge represents the probabilistic dependencies of variables (Pearl, 1988). In order to implement the learner modeling using Bayesian networks, the learner characteristics such as knowledge, error, motivation, needs, and preferences are represented by nodes (Millan et al., 2010).

As per the investigation of learner modeling approaches used in the literature by researchers/academicians, following results are presented, considering a total of 70 existing tutoring adaptive systems (Chrysafiadi and Virvou, 2012). Figure 2.1 presents, the graph of total number of ITS/adaptive/e-learning systems plotted against the different learner modeling techniques or approaches that have been used for implementation of their learner modeling. This reveals a higher use of 'overlay' and 'Bayesian techniques' in ITS development, as against the other modeling approaches.

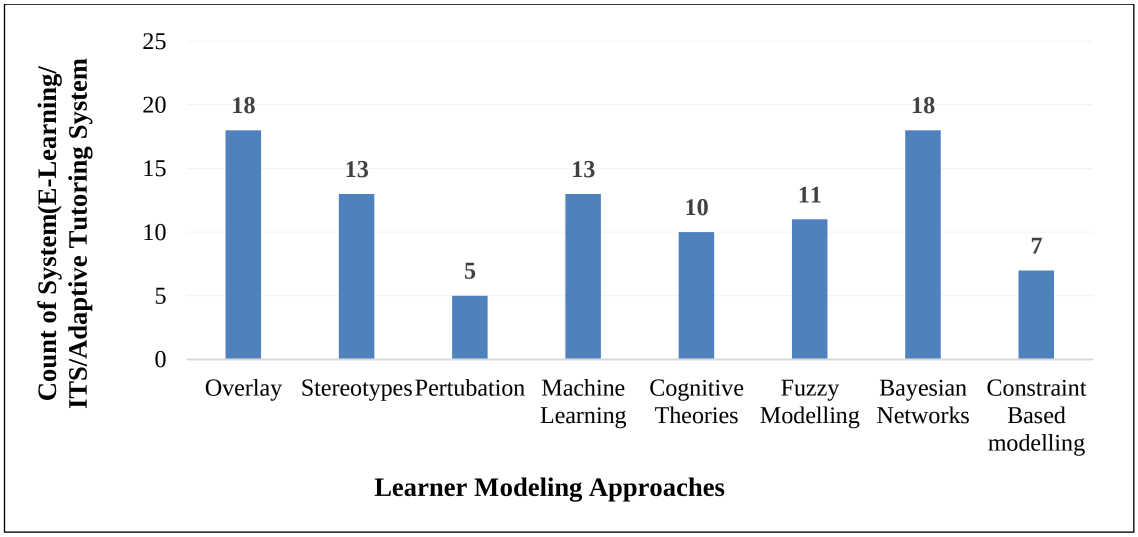


Figure 2.1 – Comparison of different modeling approaches in use in various Systems (E-learning/ITS/Adaptive)

2.3 LEARNER CHARACTERISTICS/ATTRIBUTES

The learners are very distinctive and have individual choices and needs, for example, earlier information, individual interest, abilities, learning styles, intellectual and meta-psychological aptitudes, etc. Every learner wants to learn in his/her own individual way based on their competency and background. Therefore, it is important to recognizing the learner characteristics during initialization and implementation of learner model. Some questions must be answered like "Which are the significant parts of student that should we model in an ITS?" during development of adaptive learner model (Gonzalez, Burguillo, and Llams, 2006).

So as to actualize the learner model, the static and dynamic characteristics of learners needs to be focused. Static attributes are characterized by the individual subtleties, for example, name, email, language, and age, etc. These static details could be gathered through the survey before tutoring commences and stay unaltered during the mentoring meetings (Jeremic et al., 2012). The dynamic characteristics also termed as performance features, competency levels, and learning style etc. are collected during the tutoring session. Therefore, the challenge is to analyze the learner dynamic characteristics that constitutes the base for adaptation of the system.

According to Ozyurt and Ozyurt, 2015; Troung, (2015), learning style characteristics play an important role for determining the individual differences and could be adopted to developed adaptive learner model. According to Keefe et. al. (1990), and many studies (Tseng et al., 2008; Graf et. al., 2010, 2009) reveals that, adaptive systems based on learning style provides higher satisfaction level and learning outcomes in terms of learning gain

Based on investigation of learner characteristics used in the past by researchers, following results are presented, considering a total of 70 existing tutoring adaptive systems (Chrysafiadi and Virvou, 2012). Figure 2.2 presents the graph of total number of ITS/adaptive/e-learning systems plotted against the various learner characteristics that have been used for learner adaptability. It indicates that 'knowledge level' has been most widely used learner characteristic so far, in ITS development.

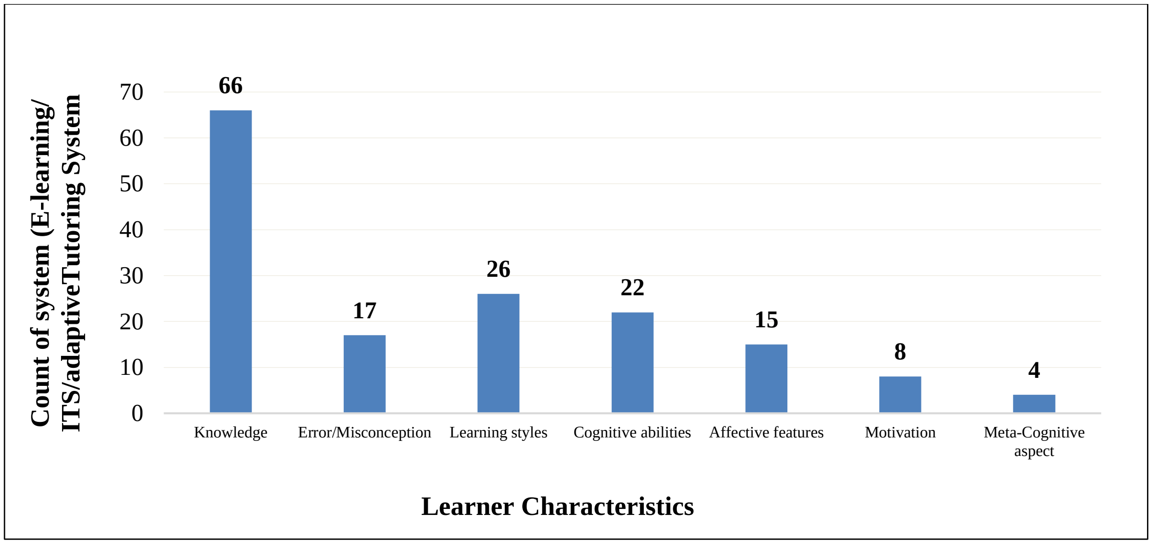


Figure 2.2 – Comparison of different learner characteristics in use in various systems (E-learning/ITS/Adaptive)

2.4 LEARNING STYLES AND MODELS

2.4.1 Learning Styles

Learning Style has no single definition, in a significant part of the writing it is utilized freely and frequently reciprocally with terms, for example, 'thinking styles', 'psychological styles' and 'learning modalities'. Research in the field of learning styles is clashing and frequently methodologically imperfect. The writing draws on the fields of instructional method, brain research, and neuroscience, yet largely, neglects to connect with completely with any of them. There are various hypotheses and feelings on learning styles, however, few by and largely concurred actualities. A few specialists underscore the significance of working memory or tangible pathways in deciding how learners learn, while others subscribe to the possibility of numerous insights. An absence of scholastic lucidity and the contending business interests in the field have prompted a befuddled and confounding exhibit of ideas, models, and instruments. Some are more compelling than others are, yet no model of learning styles is all around acknowledged.

A learning style is portrayed as the characteristics, attributes, and tendencies in which people sense, get and decipher the data (Corich, S., Kinshuk, H. L., and Lynn, M. 2004). It implies the way that every individual has own specific system, strategies or set of techniques while learning. Learning style as a scholarly capacity, emotional attributes, and mental practices that fill in as commonly stable markers of how students see, interface with and respond to the learning condition.

James, W. B., and Maher, P. A. (2004) presented, a learning style is preferences to learn and a condition under which, learners most valuably and appropriately watch, procedure, store and remember what they try to realize. After knowing learners learning style, instructors could plan the mentoring methodologies and presents the best-suited learning resources and material (Felder and Silverman, 1988). Index of learning style questionnaire defines the learning style dimensions on a scale from +11 to -11 . Felder and Silverman, (2005) presented an Index of learning style survey questionnaire based on some learning measurements on a scale from +11 to – 11.

2.4.2 Learning Style (LS) Models

Recent research focus is to examine the literature on learning style models and to propose a novel learning style model for the adaptation in the ITS. Each LS model proposing diverse depictions and characterizations of learning dimensions has been examined. As indicated by Coffield et al. (2004), Above 70 cognitive and LS models and identified thirteen of them as significant or influential models. These learning style models have a hypothetical significance in the field, are utilized most, and have a high impact on pedagogy. Moreover, lot of research has been done over the most recent three decades concerning distinctive aspects of these learning style models.

This section introduces ten mostly utilized learning style models, their definition, and limitations (Coffield et al., 2004). The appropriateness of the LS models in an innovation has been considered as an imperative foundation, including the use of learning style models in effectively existing frameworks and additionally their capability to be utilized as a part of a framework. Since this postulation concentrates on learning styles as opposed to on subjective styles, models that measure the intellectual capacities and aptitudes instead of self-announced learning inclinations have been barred. Thus, the review of ten learning style models with limitations is being explored below.

Briggs Myers presented the Myers-Briggs Type Indicator [MBTI] in 1962, proposed an identity test that was not centered particularly on identifying the learning style. Notwithstanding, the learner identity impacts learners preferred method for the learning and in this way, MBTI incorporates critical viewpoints for learning. The MBTI learning style inventory is exceptionally prominent and in broad utilize. The MBTI depends on four bipolar divisions speaking to stable identity sorts and collaborate with each other rather at that point being autonomous, and for a total portrayal of an individual's type, the mix of every one of the four inclinations should be considered (Myers et.al., 1985). The limitation of this model is the, it provides vague implication for the pedagogy recommendation and not good to predict the learner performance.

Dunn and Dunn's model (Dunn and Griggs, 2003) is considered by Coffield et al. (2004) to be one that presents cognitive style and inclination from a low-level, base up perspective of individual learning attributes, (i.e., learning styles as unavoidably focused highlights in light of hereditary qualities, characteristic legacy, and the association of identity with intellectual procedures). Dunn and Dunn are never acknowledged that the environments may affect such cognitive skills, yet their structure imagines such attributes as steady ones working alongside adaptable and tradable qualities. Dunn's incorporates five factors (environmental, sociological, emotional, physical and psychological) where each factor comprises of a few components (Dunn and Griggs, 2003). The Learning Styles Inventory [LSI] was created for kids and comprises of 104 questions (Dunn et al., 1996). The Building Excellence Inventory, it incorporates 118 questions to identify learning style. This model is very simple and widely accepted in pedagogy development but it does not have an appropriate connection with the neuropsychology to psychology.

Gregorc's learning style model is based on the mental processing and depends on two measurements managing the preferences for perception and ordering (Gregorc, 1982a; Gregorc, 1982b; Gregorc, 1985). Considering the perception, individuals can favor abstract or concrete method or some blend of both. The ordering measurement manages the way a student is organizing and utilizing data in either a sequential or random request, or in a mix of both. The perception and ordering measurements can be joined into four fundamental intercession channels which prompt four sorts of students (Gregorc, 1982a; 1982b). This learning style theory is unclear and uncertain, and psychometric apparatus has gotten significant negative feedback with respect to unwavering quality and legitimacy.

The Kolb theory of learning style (Kolb, 1984), learning is defined by four-stage cycle. As indicated by this hypothesis, students require four capacities for powerful. Kolb, D. A., & Fry, R. (1975). produced the Learning Style Inventory (LSI) and updated many times (Kolb, 1999) to identify the learning style of learner. The present variant of LSI (Kolb and Kolb, 2005) utilizes a constrained decision positioning technique to evaluate a person's favored methods of learning. This theory is based on the explicit assumptions and has fair historical reviews. It has a limitation, the learning cycle of this theory is arguable with indecisive findings.

Riding and Rayner (1998) presented the Riding Cognitive Styles Analysis (CSA) model, that is a case of psychological learning styles that consider learning styles as auxiliary properties of the intellectual framework itself. According to CSA (i) a cognitive style is the people favored and a continual way to deal with sorting out and speaking to data, and (ii) a learning technique is the procedure used to react to the requests of a learning setting. The cognitive or Intellectual style is stable and inherent components of the individual personality, while the technique to model them may vary (Riding, 1997). CSA model defines the two axes of cognitive style analysis i.e. verbalizer-imager and holistic-analytic axes. These two axes are viewed as free of each other. This theory may have strong implications for the pedagogy but it is biased towards one dimension of learning that would be the drawback for the learner.

The Felder-Silverman learning style model is characterized using the four distinct measurements. This model elaborates, how learners prefer to perceive, process, understand and receive the information (Felder and Silverman, 1988). Felder and Silverman show dimensions of learning style by utilizing scales from +11 to - 11 for each measurement. Therefore, the learning style of every student is described by four esteems amongst +11 and - 11, one for every estimation. For identification of learner learning style, the ILS instruments is used, that contains forty four questions (Felder and Soloman, 1998). This learning style model focused only on the engineering education and has several questions, occasionally leading to student boredom.

Honey and Mumford (1982) model is similar to the Kolb model (Kolb, 1984). It is based on four dimensions i.e. activist, theorist, pragmatics, and reflectors. Honey and Mumford (1982) refers the Learning Style Questionnaire (LSQ) to identify the learning style, and was revised in 1992, 2000 and 2002 (Honey and Mumford, 1992; 2000; 2002). The LSQ of Honey and Mumford (2000) comprises of 80 questions, separated in four squares of 20 questions, with each piece coordinating the four learning styles specified previously. This model provides a good suggestion for improving learning preferences and exactly says how a learner learns. This model is a poor predictor of the performance in relation to the preferences.

The Apter's Motivational Style Profiler (MSP) model is one of identity sorts that impact learning inclinations and styles (Apter et. al, 1998; Apter, 2001). Apter's model is based on the reversal theory of learner's personality type. As indicated by this hypothesis, individuals are driven by motivational states that can be comprehended as captivated mental needs and styles of collaboration with the world. The MSP is made out of psychometric scales and sub-scales, with ranges made up of two attributes that incorporate hopefulness and cynicism, reality and energy, being aggressive and tender, having a self- versus other introduction, and so on. Apter's model could be an alternative for the fixed traits, it does not measure the learning style and not further research in the pedagogy development.

The Herrmann learning style model, (Herrmann, 1989), is known as brain model theory provided by the Sperry (1964). According to this theory, the structure of the human brain is divided into two parts, north, and south cerebral hemisphere. The Herrmann "Entire Brain" model recognizes four modes or segments i.e. segments A, segment B, segment C, and segment D. The Herrmann Brain Dominance Instrument (HBDI) was used to recognize the learning style in a preferred segment of the hemisphere. It is a self-report inventory with 120 questions (Herrmann, 1989). This theory does not concentrate on the pedagogical application.

Jackson's Learning Style Profiler (LSP) imagines his model as a subset of identity factors, in view of natural limitations and roused by neuropsychological hypotheses and ideas (Jackson, 2000; Jackson et. al., 1992). Jackson proposes four learning styles as parts of the broader identity sorts: the initiator, the reasoner, the investigator, and the implementer. Dissimilar to Honey and Mumford (2000), and Kolb (1999), Jackson does not conceptualize his learning styles as subject to a learning procedure or cycle; rather, they are settled identity qualities, which are showed by people, and each has its qualities and shortcomings. The LSP comprises of 80 items, separated in the four dimensions of 20 questions each for each learning dimension specified previously. The Jackson profiler provides a recommendation for personality advancement and it is a hypothetically good instrument. The reasoner dimension is very poor for pretest, and this model is stable for the personality types.

2.4.3 Summary of Learning Style (LS) Models

This sub-section presents a summary of learning style models in view of the audit of Coffield et al. The learning style models are introduced in Table 2.1.

Table 2.1 - Summary of the Review of Ten Learning Style Models

S.N.	Learning Style Models	Strengths	Weakness	Model Application	Year
1.	MBTI Model	Face legitimacy is uncontroversial, restricted proof of positive academic ramifications of coordinating learning style between students	Hazy ramifications for instructional method, not an execution indicator.	Academics Business	1962
2.	Dunn and Dunn Model	Simple and easy model. Strong implications on teaching	Less reviews. Loose connection between physiology parameter and neuroscience	Academics Business	1979 1975 2003
3.	Gregorc Model	Its focal point for neglectful emotional methods related with the processing and blend of information.	Learning style seems as an immutable feature. Theory is vague.	Academics	1977
4.	Kolb Model	It is fair model for continuous revisions and based on explicit assumptions	Learning cycle is controversial	Academics Business	1976 1985 1999
5.	Riding Model	Good implication on pedagogy. Proper evidence of linking cognitive style to pedagogical preferences	Issue in validity of model and biased toward the two poles of model	Academics Business	1991
6.	Felder Model	It is good for academics and for business.	One dimensions of this model sensing/ intuitive is confusing	Academic, Business, Distance Learning	1988
7.	Honey and Mumford	It can be used for personal development, organization, and not psychometric instruments.	Majorly not focused to cognitive ability. Not a good predictor of learner.	Business Distance Learning	1982
8.	Apter Model	It is best for the stable type of personality traits.	It does not measure learning style. No research in education	Business	1998
9.	HBTI Model	Best for the Business, theoretically sound, psychometric instruments is good to judge learning style	Lack of application on pedagogical research	Academics Business	1995
10.	Jackson Model	Best for theoretically and computerized format. Computer Recommend for personality developments. It is designed for business and academics.	Learning style is stable for personality types. The Reasoner dimensions has poor reliability.	Academics, Business, and Distance Learning	2002

2.4.4 Limitations, Criticisms, and Challenges

The learning style field is perplexing and despite the fact that part of the research has been carried out, a few imperative inquiries are not yet explored and questionable issues are under dialog. Thus, the principal challenge is to elucidate the discussions, answer the unexplored inquiries and give a reasonable comprehension of the field.

Currently, many learning style models exists in literature, each coordinating a few parts of learning, and some covering each other. Existing learning style models faced with the criticism so that there is a need for study on the most proficient method to incorporate every single dimension of learning styles. Besides, the similarities and connection between these diverse learning style models are not explained. Thus, the field leads to a challenge to conduct such research that should cover every dimension of learning styles to acquire clarity. It also needs to consider other important parameters of learning such as cognitive and meta-cognitive skills. The experimentation validity of models is not explained. Subsequently, a validation of the learning styles field is to lead inquiry, assess them to distinguish significant learning style models/measurements, and build up a comprehensive model that coordinates every single pertinent part of learning styles.

Moreover, the dubious issues about learning style are, Is it the fixed characteristics? Or Is it change over time? Thus, the subjects and conditions need to be cleared. Contingent upon the essential thoughts behind the learning style models, scholars make diverse cases for the steadiness inside these models.

Another criticism manages the ramifications of learning styles in teaching. While the adequacy of the coordinating methodology is by all accounts instinctive and the most famous proposals, upheld by instructive speculations, conflicting outcomes are gotten by studies, impacts on accomplishment while giving coordinated and confounded guidelines to students with various learning styles.

Reynolds (1997) said the principal criticism with respect to the coordinating methodology is that it is essentially "doubtful", given the requests of adaptability it would make on educators and mentors". In classroom learning environment, the instructors would need to routinely change their instructing style to suit the diverse learning styles of learner. Consequently, the feasibility of the pedagogy coordinating methodology is relying upon the embraced learning style model and the quantity of learners in the class.

Coffield et. al. (2004), most fervent feedback identifies with the affirmation that learning styles should be huge to a specific degree that issues for training and teaching method (i.e., approval information indicate significant impact sizes). The summary of criticisms compiled by the Coefield et al. is presented below

- The presence of some hypothetical incoherencies and confusion in the concept also, factorial outlines of such construct.
- Practical issues identified with learning styles, for example, naming and stereotyping, and in addition a few personal stakes from the creators.
- The variable nature of learning style models.
- Widespread psychometric shortcomings got from the learning style models.
- The outlandish confidence put in straightforward inventories.
- No unmistakable ramifications for teaching method.
- The absence of correspondence between various research points of view on teaching method.

2.5 DOCUMENT ANALYSIS OF LEARNING STYLE MODELS FROM 2000 TO 2017

Learning through the web mentoring framework gained speed due to the enhancement in internet technology in recent decades. Learning is a very complex process and each learner is different and their preferred way of learning. Some learners prefer to learn through textual information and others may prefer to learn through the experimental analysis by examples and some may deal with the interpretations of information through imagistic approach. The examinations on making learning situations dependent on interest in learning styles have picked up significance lately. Learning styles are one of the most significant boundaries or characteristics in deciding individual way of learning and preferences (Herod, 2004).

The learning style referred to as a student's favored method of learning and could assume an important role to provide the adaptivity in a web-based mentoring framework. There have been a number of studies concentrated on the inclinations and learning style of students in recent decades. Learning style speculations and their applications have been utilized by and by in mid-2000 in the various fields (Ozyurt et. al., 2015). These days, numerous instructive establishments, universities, and colleges lean toward showing utilizing e-learning courses. There is little center given to the learner requirements, decision, and qualities of individual students and thusly, all students are treated in the same way. Therefore, the main focus of this current work to the development of an adaptive tutoring framework that can accommodate learners learning styles.

The significance of learning style is versatile and numerous learning style models exist in the literature that addresses the different innovative enhancements that have promising implications (Shih et. al. 2008). The framework can offer important guidance and directions to learners and instructors to enhance their learning procedures after knowing students learning styles. For instructors, it will have the option to offer important suggestions on the most proficient method to coordinate reasonable guidelines and learning materials to various learners at the proper phase of the learning procedure (Stash, N. (2007).

According to (Lee and Park, 2008), adaptability and adaptivity are interchangeably used in the hypermedia education system to provide personalized learning in the literature. The key point in designing and developing adaptive learning conditions is making variation dependent on what is to be taken as a reason for adaptation (Liegle and Janicki, 2006). Learning style is generally referred to as the choice of learning in different environments (Veznedarog lu & Ozgür, 2005).

This examination foresees to add to the choices of the current conditions, and such investigations that are required here, its application, the effect of learning style on adaptive mentoring framework, and the current inclinations in the field. Additionally, it has a colossal examination, it intends to choose the current examples about an adaptive framework considering learning styles and existing literature gaps, which will prompt for the future examinations. The critical content analysis helps the researchers to add improvements in the existing tutoring framework. So alongside this, the point of this critical examination is to do a broad investigations of literature concentrated on taking in styles of student distributed from 2000 to 2017 and answer the going with research questions.

1. What are the principle center, reason, research type, and technique for investigation of AITS tending to learning style?
2. What are the sorts of members/participants and their competency levels, region/field of particular domain and information gathering instruments utilized?
3. What are the application of learning styles and models, learning style identification algorithm and classification that have been utilized in AITS?
4. What are significant discoveries and synopsis concerning learning styles as a characteristics or attribute of student?

2.5.1 Research Methodology, Purpose, and Search Techniques

The present work examines the mentoring framework based on the learning style and a critical content analysis was conducted using the document analysis published since approximately two decades. The content analysis is portrayed as methodically arranging, ordering, taking a gander at substance and securing results from writing (Ary et. al., 2006). The reason behind picking the archive examination technique is that, this joins data which are like each other taking into account explicit thoughts, strategies, purposes, and applications. An assortment of examination is being done in this field. The majority of them can be ordered significantly in three distinct measurements, for example, research methodology, methods, search techniques. These are being discussed in the upcoming sections.

Exceptionally, due to the advancement in web innovation, the growth in the field of the adaptive mentoring framework has gained for two decades (Modritcher, 2008). A critical review of the literature was conducted over electronic repository and many journals and web databased have been examined. The electronic databases and libraries include a web of science, scholar thesis, Science Direct, Elsevier, Google Scholar, Springer, and numerous other web links that exist in the quality articles. The content analysis was focused on some keywords like “learning style”, “learning preferences”, “E-learning”, “hypermedia system”, “adaptivity”, “adaptation”, “web-based system”, “tutoring system”, “adaptive hypermedia”, “learner model”, “customized learning system”, “personalized tutoring system”, “learner modeling”, “user modeling”, “intelligent mentoring framework or tutoring systems” have used.

2.5.2 Including/Excluding Method

The critical analysis is conducted focused on the learning style and models used in the web based tutoring framework. Many articles were examined that incorporated the learning style characteristics to develop an adaptive framework. Over 120 articles have been critically examined and an extensive survey was conducted to get the best inferences. The clarification behind the incorporation/avoidance was that these assessments that relied upon a comparable learning style and competency, are kept independently for secluded examinations. Since certain articles were isolated that could be requested as exploratory approval of AITS adequacy, we decided to fuse speculative proposals of such systems moreover, in which it was suggested that further examination should focus on accurate exploration discoveries.

2.5.3 Data Gathering and Analysis

Archive investigation covering a few articles has been directed. The data was arranged dependent on frequencies and rating of articles. The gathered writing is explored in the light of exploration addresses illustrated before in this work. The second part pf this investigation, research findings in terms of outcomes have been discussed, under many parameters, for example, categories, reason, type of research, procedure. The research was focused on the type of students or participants, their competency level, domain area, and many data accumulation tools, based on learning style in mentoring framework, application of LS and LS classification algorithms, findings. This systematics of information was attempted to guarantee simplicity of examination and reaching important inferences.

2.5.4 Results

The critical analysis of document published between year 2000 and 2016 based on web mentoring system was conducted and examined. The document analysis reveals over 70 article and research papers. Various measures have been distinguished to bunch these investigations and results have been arranged. For a significant examination and simplicity of portrayal, a lot of standards have been taken as one gathering and talked about under one heading. Thinking about measures, under a gathering, the all number of studies are assembled, indicating their examination brings about plain arrangements. In the current paper, five arrangements of models are introduced from area 2.5.4.1 to 2.5.4.6. Each set holds a rundown of models, which have been utilized to aggregate the examinations and speak to the correlation quantitatively as rate.

2.5.4.1 Main focus, purpose, research type, and technique for investigation of AITS tending to learning style.

The summary of content analysis under the measures “main focus”, “study purpose”, “research type”, and “methods/techniques” is presented in Table 2.2. Considering the measure “main focus”, as a total of 78 investigations were incorporated and analyzed. Out of 78 studies, 63(80.76%) were directly focused on providing the adaptation based on the learning style of learner, while the remainder of 15(19.24%) contemplates concentrated on different characteristics of the learner. The investigations uncover that a larger part of the tutoring system considers learning style as a base for adaptivity.

In addition to that, considering the measure “study purpose”, out of 78 investigations 27(34.6%) studies were focused on proposing the tutoring model concentrated on adaptations. 13(16.65%) of the studies reveals that the key role of learning style in the development of an adaptive tutoring framework. 12(15.39%) of the studies focused on the usefulness of and adoption of AITS in terms to provide the satisfaction level of learners. 10(12.83%) of the studies reveals that the impact of the adaptive mentoring framework on academic achievement in terms of learning gain and outcome. 6(7.68%) out of 78 studies addressed the learning style model that automatically predict the learning style of learner. 8(10.24%) studies addressed measuring the effectiveness of AITS and 2(2.58%) studies were involved in some other parameters or characteristics of the learner.

Furthermore, considering the "type of research" associated with the study, 19(24.34%) out of 78 studies, were centered around the hypothetical idea and no reasonable proof was found. 12(15.36%) of the studies were addressed the practical approach and used empirical research to find the quantitative relationship and inference between learning patterns of numerous learners. Finally, 47(60.26%) of the studies evaluate the performance of learners in terms of their learning gain. Moreover, out of 78 studies, 33(42.30%) were used experimental approach and 45(57.70%) of the studies used the case studies.

Table 2.2 - Summary of Main focus, purpose, research type, and technique for investigation of AITS tending to learning style.

		Frequency(f)	Percentage (%)
Main Focus (n=78)	Adaptivity based on learning style	63	80.76
	Other	15	19.24
Purpose (n=78)	Proposed model of ITS based on Adaptivity	27	34.60
	Learning Style impact on Adaptivity	13	16.65
	Determining the usability, learner level of satisfaction	12	15.39
	Impact of adaptive tutoring system on academic achievements/ learning outcomes	10	12.83
	Model for automatic learning style prediction	6	7.68
	Effectiveness of AITS	8	10.24
	Other	2	2.58
Research type (n=78)	Theoretical	19	24.34
	Empirical studies	12	15.36
	Learner evaluation	47	60.26
Techniques (n=78)	Experimental	33	42.30
	Case studies	45	57.70

2.5.4.2 Type of participants, their competency levels, subject area/field and data accumulation tools

Concerning the subsequent research question, types of participants, their competency levels, branch of knowledge/field, student modeling and tools, and information gathering tools utilized in the investigations distributed between the year 2000 and 2017 were analyzed. The summary of the content analysis under these parameters is presented in Table 2.3.

As shown in Table 2.3, an aggregate of around 63 participants was involved in the experimental review of studies. Considering the measure "participants", 52(82.53%) were students, 7(11.10%) were teachers/instructors and 4(6.35%) belonged to both of the titles. As an interpretation of the results of "participant types", the majority of the leaners were students who were key participants of using tutoring systems. In addition to this, considering the measure "competency level" or "participant's level", an aggregate of 73 studies were examined. 53(72.61%) out of 73 belonged to the higher level of study and engineering backgrounds, 6(8.21%) belonged to the secondary level of education, 4(5.6%) belonged to the elementary level of education, and finally, 10(19.70%) were a mixed type of participants with different education level.

Furthermore, considering the measure "learner modeling", a total of 59 studies were involved and examined. The static and dynamic learner modeling techniques are defined in the types of "learner modeling" of learner. 40(67.80%) of the studies considered the static characteristics and used static model technique to development of learner model, while 19(32.19%) very small studies used the dynamic modeling techniques to the development of learner model.

Additionally, considering the measure "tools for dynamic modeling", 34 studies examine and interpreted. 9(26.46%) of the investigations worked on the tracking of learners behaviors during the learning, 7(20.59%) of the investigations considered the test result as a tool for dynamic modeling and to assess the learner knowledge, 6(17.66%) of the investigations considered the learner feedback to check the effectiveness of the learner model, 4(11.77%) of the studies considered time spent on tutoring system or to complete any exercise as a tool for dynamic modeling, 3(8.83%) of the studies used the profile based selection tools for dynamic modeling and offered the learning material according to their profile, and finally, 5(14.71) of the investigations considered the mixed type of learner modeling techniques and tools. These perspectives recorded here, for example, student conduct, test result and input, time spent on learning material, distinguishing singular profile have all been considered here as the 'instruments' that have been utilized for 'dynamic modeling' inside the tutoring framework.

Moreover, considering another measure “data gathering tools”, 134 studies were engaged in the examination and investigations. 55(41.03%) used learning style inventory for gathering the initial learning style of learner, 26(19.41%) of the studies monitored and conducted the learner test to know their learning levels, 23(17.17%) used an online questionnaire, 14(10.46%) used system log reports, 7(5.23%) used some kind of interviews, 7(5.23%) considered the cognitive features of learners, and rest 2(1.5%) of the studies used some other inventories to collect the learner data. Finally, considering the “subject/area”, 87 studies were involved and critically examined. 47(54.01%) were from computer science and engineering domain, 11(12.65%) were from the arithmetic subject, 7(8.2%) were from chemistry domain, 6(6.90%) were from management domain, 3(3.44%) belonged to the administration, 2(2.4%) were from social science domain, 2(2.4%) were from law, and rest of the participants belongs to the unknowns domains.

Table 2.3 – Summary type of participants, their competency levels, subject area/field and data accumulation tools

		Frequency(f)	%			Frequency(f)	%
1	**Participants type (n=63)**			**5**	**Data gathering tools (n=134)**		
	Learner	52	82.53		Learning style inventory /questionnaire	55	41.03
	Teacher/Educator	7	11.10		Learning progress test	26	19.41
	Mixed	4	6.35		Online questionnaire	23	17.17
2	**Participants level (n=73)**				System log report	14	10.46
	Higher education/ Engineering	53	72.61		Through interview form	7	5.23
	Secondary education	6	8.21		Cognitive style inventory	7	5.23
	Elementary education	4	5.6		Other intelligence inventory	2	1.5
	Mixed	10	19.70				
3	**Learner Modeling (n= 59)**			**6**	**Subject area/field (n=87)**		
	Static	40	67.80		Computer science/ Engineering	47	54.01
	Dynamic	19	32.19		Arithmetic	11	12.65
4	**Tools for dynamic modelling (n=34)**				Chemistry	7	8.2
	Tracking learner behavior	9	26.46		Management science	6	6.90
	Test result	7	20.59		Administration	3	3.44
	Learner feedback	6	17.66		Social Science	2	2.4
	Time spent	4	11.77		Law	2	2.4
	Learner selection based on profile	3	8.83		Domain independent/ Undermined	9	10.32
	Mixed	5	14.71				

2.5.4.3 Application of learning styles and models, learning style identification algorithm and classification that have been utilized in AITS?

Concerning the subsequent research question, application of learning styles and models, learning style identification algorithm and classification that have been utilized in AITS have been investigations distributed between the year 2000 and 2017 were analyzed. The summary of the content analysis under these parameters is presented in Figure 2.3.

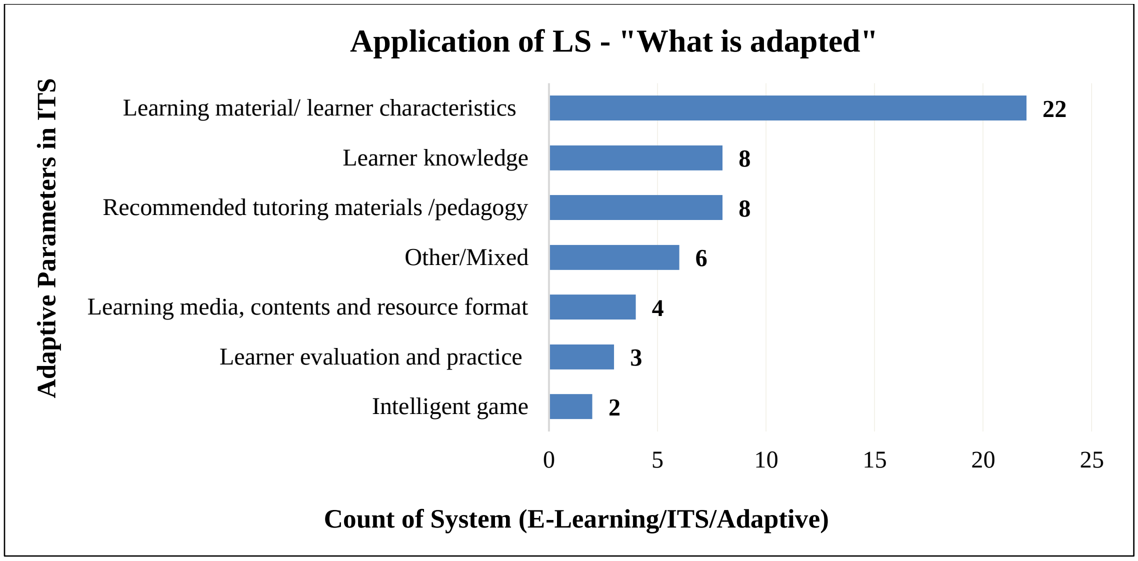


Figure 2.3 – Comparison of different learning adaptive parameters use in various systems (E-learning/ITS/Adaptive)

A systematic study have been conducted considering the parameters for example, learning style model, learning style identification algorithm, and learning style classification algorithm. While a few articles have used one method for recognition/distinguishing learning style of learner, most others have utilized blend techniques to give adaptivity dependent on learning style. The studies reveals that learning material and learner characteristic is one of the parameter that is adopted during the development of adaptive tutoring system.

The following Figure 2.4 represents the learning style classification techniques used in the web mentoring framework. After a critical review more than 45 studies has been examined and investigated and more than 8 classification techniques used by the researchers. Considering learner style classification algorithm in the tutoring system, 17 articles used rule-based classification techniques and this is one of the most popular methods that help the system to provide the adaptivity. In addition to that, Bayesian network was the second well know technique that work on the concept of Bays theories (Garcia et al. (2007). While 5 investigations utilized the Naïve Bayes strategy and ANN. 3 investigations utilized choice tree strategy, 2 of the examinations utilized Markov and Reinforcement model, 1 investigation utilized Genetic calculations, and a rest of 7 of the investigations utilized, different procedures or blended strategies for learning style grouping.

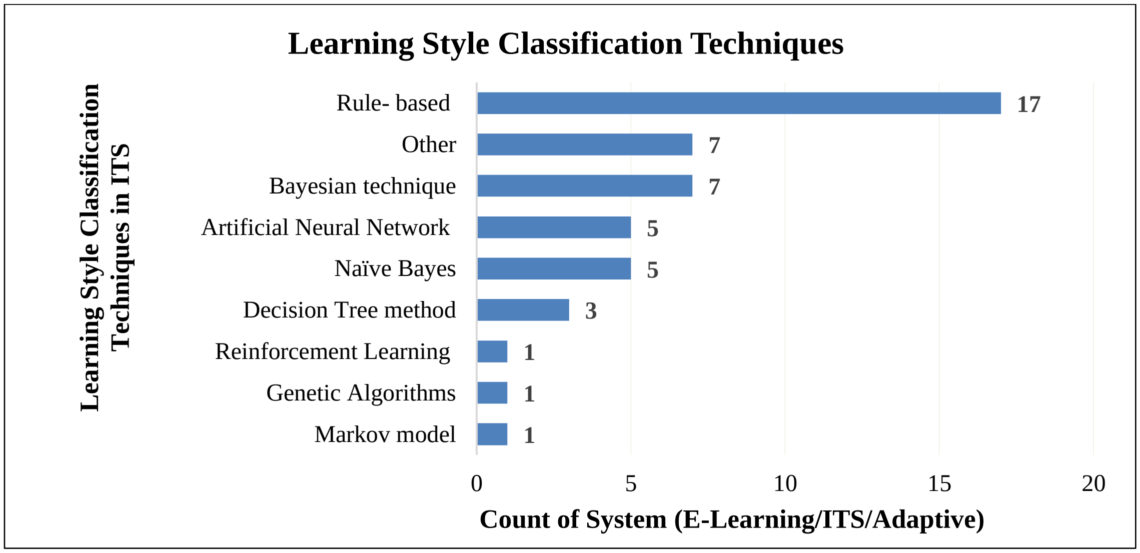


Figure 2.4 – Comparison of classification techniques use in various systems (E-learning/ITS/Adaptive)

2.5.4.4 Learning style model used in AITS

With reference to the next subsequent question, Over 70 studies were examined and 44 studies have been used the learning style model in the development of the tutoring system. Figure 2.5 summarized the learning style model utilized in the adaptive tutoring system. After a critical analysis, the study reveals that the Felder model of learning style was mostly utilized in AITS. Out of 44 studies, 30(68.18%) of the studies utilized a Felder learning style concept to the development of the learner model, which shares the highest percentage. 4(9.09%) of the studies used the Kolb model, 3(6.81%) of the studies used the Honey and Mumford model, 2(4.54%) of the studies used the VARK and MBTI model each, and rest 3(6.81%) studies used some other unidentified learning style model.

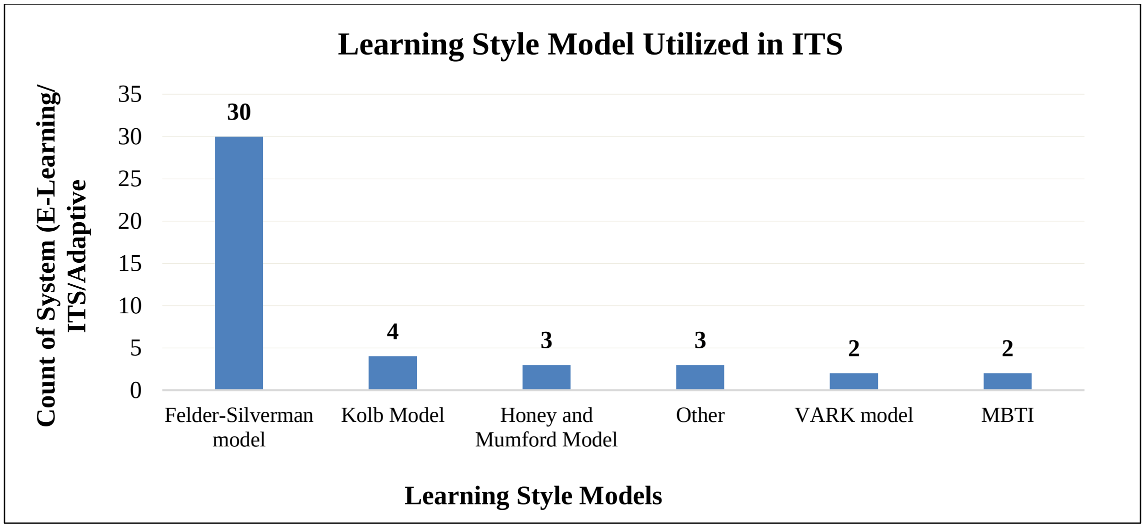


Figure 2.5 – Comparison of common learning style models utilized in various systems (E-learning/ITS/Adaptive)

2.5.4.5 Findings

Concerning the last examination question, revelations, and blueprint of the surveys on adaptive mentoring frameworks from 2000 to 2017 is presented in this section. The study was totally centered around the use of learning style to make tutoring framework adaptable. After a critical document analysis and investigations, some findings were inferences. In addition, it very well may be accounted for that there are high positive conclusions concerning student achievements and ease of use with these circumstances and their effect on scholastic achievements just as their learning inclinations and necessities. The general finding has been grouped under ten primary titles as appeared in Table 2.4. Seven of these show positive planned towards adaptive framework while rest demonstrate negative forthcoming. The positive discoveries have a biggest share (n= 95; 90.47 %) and negative discoveries are (n= 12; 9.52%) which is exceptionally constrained or less.

The summary of the findings of the study in terms of result is presented in Table 2.4.

Table 2.4 - Rundown of Findings in the Analyzed Studies

		Frequency (f)	Percentage (%)
positive perspectives (n=95)	Learner satisfaction, preferences, usability, and adaptivity based on learning style	30	28.57
	Correct prediction learning style	13	12.38
	Relationship between learning style and other learner characteristics or navigation	8	7.62
	Positive effect on learner learning	18	17.14
	Positive effect on learning achievements	15	14.29
	Positive effect of learner modelling	11	10.48
Negative perspectives (n= 10)	No correct prediction of learning style	5	4.76
	Not making constructive outcome on academic and learners achievements	3	2.86
	No effect on learner modeling	2	1.90

2.5.4.6 Discussion and Outcomes

The current study was totally focused on the utilization of learning style in web based tutoring system. This study is huge in light of the fact that it advances essential discoveries in regards to the improvement of numerous zones, for example, adaptive hypermedia, different types of subject domains, types of participants, learning style classification techniques. This study opens the door for new researchers who are willing to work of learning style and models to fulfill the existing gaps in the literature. Referenced to the research questions, the outcome and finding are summarized in this section.

Considering the section 2.4.4.1, the finding reveals that, the empirical research contributes a key role to provide the adaptivity in web framework. The finding of section 2.5.4.2 reveals that, dynamic modeling techniques, and dynamic learner parameters were play an important role for adaptivity. The learning style poll is for the most part utilized to know the learning style. The Section 2.5.4.3 uncovers that learning style is generally used to: give versatile learning materials to the student, prescribe the most appropriate teaching method and to give right assessment of the student to improve the viability of the mentoring framework.

The commitment of this exploration seeing isn't just as a guide for the adaptive mentoring framework, yet in addition serves to improve the adequacy of the learning style classification techniques. The finding in Section 2.5.4.4 uncovers that Rule based classification was the most adopted algorithm in AITS.

The discoveries in Section 2.5.4.5 uncovers that, obliging learning styles in the wise mentoring framework makes learning simpler, compelling and expands student fulfillment levels towards learning. The positive point of view for obliging this broke down examination dependent on the learning style in AITS holds the biggest portion of about 90%, and holds an extremely constrained negative viewpoint for example about 10%.

2.6 PROPOSED TUTORING SYSTEM - 'SEISTUTOR' VS. EXISTING TUTORING SYSTEMS

The computerized educational framework is the favored route for giving the customized learning materials to students and has the points of interest to offer the self-guided student driven directions anyplace and whenever.

Intelligent Tutoring System (ITS) is a broad research area with many of its aspects ranging from system development, its architecture, to its evaluation and its several applications that have been explored, and re-explored. Elaborate research work is being conducted in this field. The work in this thesis is novel and has been compared with some of the existing tutoring systems. The proposed tutoring system has been compared with three existing tutoring systems i.e. 'Shikshak', 'SQL-Tutor', and 'AG-TUTOR'. The developed tutoring system 'SeisTutor' presents several novel aspects that are as under:

- ITS has, different components – Student/Learner Model, Expert Model, Pedagogy Model, Domain Model, and Presentation Model. The focus of the existing work in the tutoring system- 'Shikshak' is on the domain model (Chakraborty, S., Roy, D., & Basu, A., 2010). The 'SQL-Tutor' has been focused on the knowledge about the domain that is represented as a set of constraints and the student model is implemented using the Constraints Based Modeling (CBM) approach proposed by Ohlsson (1994). The 'AG_TUTOR' is focused on designing of Domain and Expert Module. The domain model is developed using the key vocabulary and relationship among all the concepts, whereas, in present work, the focus is on the Learner model. The two learner characteristics that have been a central focus in our work are the learning level (competency level) and learning style.

- Shikshak (Chakraborty S. et al., 2007) system has been developed for tutoring a typical programming language and focus is domain model, predominantly, on organizing the domain knowledge using trees/directed graphs. The SQL Tutor (Mitrovic et al., 2013, Mitrovic, A., 2003) has been developed for tutoring SQL database queries and no standard data structure is used for the organization of domain model. The AG_TUTOR (Mahmoud, M. H., and El-Hamayed, S. H. A., 2016) has been developed for tutoring the grammar of the Arabic language, whereas, in 'SeisTutor', the system developed is for tutoring a subject matter, related to an experiential field. The field is 'Seismic Data Interpretation', which is the knowledge of interpreting seismic images to reveal the subsurface geology. One of the research aspects involved in this system is elaborate survey work to explicate this knowledge, as there are no interpretation rules available.

- In the existing system 'Shikshak', the cognitive abilities, limited to comprehension-ability and problem-solving abilities have been used to tutor the student, and to adjust the tutoring based on the performance. The existing tutoring system 'SQL-Tutor' and 'AG_TUTOR' have used the knowledge and their abilities to observe students' actions, whereas in present work we have developed a novel Learning Style model. It has been named, I2A2 Learning Style Model, with four learning styles, the dimensions, Intuitive, Imagistic, Acoustic and Active. Along with this model, inventories on the learning style question pool, have also been developed. This is one of the main contributions of the work.

- In the existing work 'Shikshak', an authoring tool is embedded in the developed ITS, to support the feeding of ITS with the new subject matter. The authoring tool is one of the main significant components which is connecting with all other components of ITS (Bhattacharyya, T., & Bhattacharya, B. 2013, 2015). The 'SQL-Tutor' uses the knowledge of learners to feed the learning materials and curriculum sequencing technique to provide the appropriate sequence of topics. Active and passive curriculum sequencing is used to offer suitable learning material, whereas, in our work learner performance parameter and learning style of learner have been used to adjust the pedagogy.

- A significant part of our thesis revolves around learner identification and classification. For this purpose, we have developed learner classification and learner adaptation algorithms, have used static and dynamic features of learners, and have a full-fledged pre-tutoring phase in the ITS product, which generates learner profile. Learner profiling helps to offer a personalized and adaptive tutoring strategy to the learner according to their stereotypes. As mentioned earlier, the learner model has very limited coverage in the existing work – 'Shikshak'.

- We have also developed inventory for the Learner Feedback Questionnaire (LFQ), which is another novel contribution of our work.

- Lastly, the evaluation process used in our work is different from the one followed in the work done in existing ITS. Using the LFQ devised for this purpose, we have identified, five system evaluation parameters, which are, system effectiveness, adaptability, personalization, system support, ease-to-use. Categorizing responses, under these parameters, we have quantitatively analyzed the efficiency of the system, to achieve its tutoring objectives.

- Further, the concept of hints, lesson revision has been built in our system, to ensure effective learning. These have not been used, in the existing systems 'Shikshak', 'SQL-Tutor', and 'AG_Tutor'.

Our entire focus was on researching within the system, covering learner modeling, learner models, etc. than the ITS systems developed so far, their variants, their features, etc.

The proposed tutoring system has been compared with the existing tutoring systems and a comparative summary has been compiled under the different aspects of the system and shown in Figure 2.6. First, the Architectural Design aspects, present the architectural view of the tutoring system further segmented under the domain model, learner model, and tutoring model. Second, the System Implementation aspects, present the implementation tools such as programming language, database, and platform hosting. Third, the System Evaluation aspect, defines the different evaluation criteria, methods, techniques used in the tutoring system to check the effectiveness of the learning. This part also presents the statistical tools and validation techniques applied in the tutoring system.

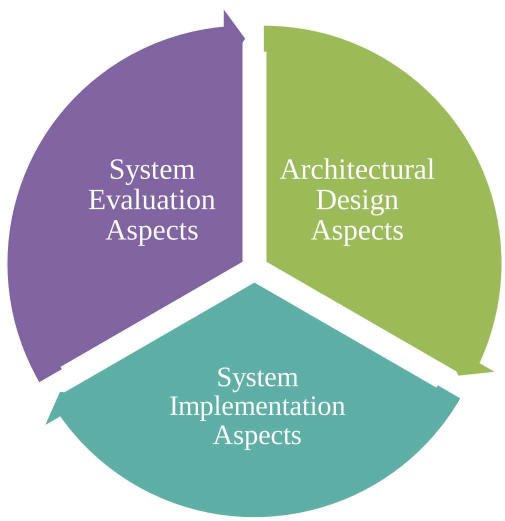


Figure 2.6: Comparison of 'SeisTutor' with select tutoring systems under different aspects.

Table 2.5 presents the Comparison of 'SeisTutor' with select tutoring systems under different aspects.

Table 2.5 - Comparison of 'SeisTutor' with select tutoring systems under different aspects.

		'Shikshak'	'SQL-Tutor'	'AG_TUTOR'	'SeisTutor'
Architectural Design Aspects	Domain Model	• Designed for ***C Programming*** language.	• Designed for ***SQL Database Queries.***	• Designed for ***Grammar of Arabic Language.***	• Designed for ***Seismic Data Interpretation (SDI).***
		• For use by ***school students.*** • Designed for rural education.	• For use by ***fresh graduate students.***	• For use by ***elementary school students*** (4^{th} Grade).	• For use by graduate seismology ***students, industry professionals, and teachers.*** • Interpreting seismic images to reveal the subsurface geology • Explicate this knowledge as there are no interpretation rules available.
		• The domain knowledge is organized using ***graph/tree*** data structure. • ***IEEE LOM*** is used for learning materials (IEEE LOM, 2002). • Used a repository for learning material.	• ***No data structure*** is used to design and organize the domain. • ***No data model*** is used for learning repository • ***Curriculum sequencing*** is used to organize the ***domain model.*** • No approach for designing courseware.	• ***No data structure*** is used to organize the domain. • ***No data model*** is used for learning repository • No approach for designing courseware.	• A domain is organized using a ***linked and graph*** data structure. • ***The object model*** is used for the representation of the learning repository. • ***Domain Knowledge Object Model (DKOM), Domain Knowledge Database Model (DKDM),*** and ***learning repository*** are created and used. • Courseware is designed ***using a layered approach*** like layer-0, layer-1, and so on.
		• ***MS Word, PowerPoint, PDF*** files support for learning material available.	• ***No information on multimedia*** used in the design of domain material.	• Diverse types of ***multimedia*** files are not supported.	• Learning material is ***reusable and can support any standard format*** like PowerPoint, PDF, Word, Audio, Animated, and Video, etc.
		• A domain model is categorized based on ***hardness, media type, and language.***	• Domain material is not categorized according to the ***difficulty level, media type, and language.***	• ***The same type of learning materials*** is available for every learner.	• Domain material is ***categorized based on difficulty levels i.e. beginner, intermediate, and expert and different learning stylet.*** • We can ***feed new learning material and incorporated it at*** any time.
		• Covered ***limited topics*** of learning materials for the subject matter.	• Most of the part of the subject matter of the ***SQL database*** has been covered.	• ***Limited coverage*** of subject matter learning materials.	• ***A wide range*** of learning material of the subject matter has been covered.

		• Focused on ***authoring tools.*** • An ***authoring tool*** is used to customized the domain knowledge, and modify the teaching material.	• The concept of authoring tools has not discussed. • Subjective knowledge of the domain is covered.	• Focused only on the grammar of the Arabic language.	• ***To date, no tutoring system is available for tutoring the domain of SDI.*** • Not focused on ***authoring tools.*** • ***Support language interoperability.***
	Student/Learner Model	**Learner Characteristics:** • Limited to cognitive abilities. **Modeling Technique:** • Fuzzy state model **Learner Profiling:** Limited to only two attributes of cognitive ability i.e. • Comprehension-ability (C), and Problem-Solving Skills (P). • Authoring Student Model is used.	**Learner Characteristics:** • Limited to learner knowledge level only. **Modeling Technique:** • Constraints Based Modeling (CBM) Approach. • It describes ***learning from errors.*** (Ohlsson, 1994). • Declarative domain knowledge is used. • It describes the ***two phases*** of errors i.e. ***error recognition and error correction.*** • About ***600 constraints have been used.*** **Learner Profiling:** • ***No*** learner profiling.	**Learner Characteristics:** • Limited to the learner knowledge level only. **Modeling Technique:** • Production Rules Based **Learner Profiling:** • ***No*** learner profiling	**Learner Characteristics:** • Knowledge Level (Competency Level), • Learning Style and sub-characteristics. **Modeling Techniques:** • Fuzzy logic and Stereotypes Model **(Blended Approach)** **Learner Profiling:** • ***Developed Novel Learning Style Model(I^2A^2)*** with four learning dimensions i.e. *Imagistics, Intuitive, Acoustics, and Active* • ***Knowledge Level and Learning style*** are used for learner profiling.

		• ***No learner classification and adaptation*** algorithms. • ***Learner's needs and preferences*** are not considered. • ***No Learning Style*** model is used. • ***static and dynamic*** features are considered. • No Learner ***feedback***	• ***No Learner classification and identification*** algorithms. • ***The needs and preferences*** of learners are not considered. • ***The learning style*** model is not used. • Learner ***feedback*** is considered.	• ***No Learner classification and Identification*** techniques are used. • ***No Learning style*** model is used. • No ***static and dynamic*** features are considered. • ***No learners feedback***	• ***Learner classification*** using a fuzzy rule-based approach. • ***The learner classification algorithm*** is designed using fuzzy techniques and implemented in the system. • ***The learner adaptations algorithm*** is designed using fuzzy techniques and implemented in the tutoring system. • ***Learner identification*** and algorithm is developed based on their stereotypes. • ***Static and dynamic features*** are considered. • Learner ***feedback*** is considered.
		• ***No Diagnosis*** of learner errors and misconceptions.	• ***The system learns from errors*** and used the CBM approach.	• ***No Diagnosis*** of learner errors and misconceptions. • Claimed ***adaptivity*** based on questions and tasks.	• Focused on ***learner deficiencies***. • Learner ***diagnosis based on errors and misconceptions.***
	Tutoring Model	• It is called a control engine and implemented using fuzzy rule-based. • Fuzzy rules are used for decision making.	• No '***intelligence approach'*** and ***Curriculum sequencing*** are used to provide the appropriate sequence of leaning materials. • ***Active and passive sequencing*** is used.	• No '***intelligence approach'*** for implementation of the tutoring model.	• It is implemented using the '***Stereotypes' and 'Fuzzy rule-based'*** techniques.
		• It has sub-models i.e. ***topic planner, a Material selection module, and a Result analyzer.*** • ***Same pedagogy*** for every learner.	• ***No sub-model*** is available • ***No personalized*** tutoring. • ***Same pedagogy*** for every learner.	• ***No sub-model*** is available • ***No personalized*** tutoring. • ***Same pedagogy*** for every learner.	• It has many sub-models i.e. ***Administrator, Tutoring strategy, Pre-learning procedure, Lesson, Revision, Explanation, Quiz, and Hint model.*** • ***Personalized*** and ***Customized*** tutoring is available. • ***Diverse pedagogy*** for every learner.
		• ***No provision of pedagogy change*** • ***No learner-centric*** tutoring.	• ***No provision of pedagogy change***. • ***No learner-centric tutoring.***	• ***No provision of pedagogy change.*** • ***No learner-centric tutoring.***	• The provision of '***pedagogy change'*** is provided. • ***Pedagogy change algorithms*** are designed and implemented. • ***User-driven and system-driven*** pedagogy change options are offered and implemented in the system. • ***Learner centric tutoring*** has provided.

		• Material Selection module is provided. • No ***revision*** of the lesson. • ***No Hinting*** model incorporated in this model. • No adaptative and personalized pedagogy. **Authoring of Teaching Model/Control Engine:** • Used student information parameters. • Fuzzy is used for a topic planner.	• No separate model for material selection. • No ***revision*** of the lesson. • ***No Hinting*** model incorporated in this model. • No adaptative and personalized pedagogy. • Hands-on-approaches provided. • An explanation model for a lesson provided. • ***No Diverse media*** for explaining lessons.	• No ***revision*** of the lesson. • ***No Hinting model*** incorporated in this model. • No adaptative and personalized pedagogy. • Question Selector Module is used. • An explanation model for a lesson is provided. • ***No Diverse media*** for explaining the lessons.	• The tutoring strategy selection module is implemented. • ***Revision*** of learning material is provided. • ***Hinting model*** is provided to help learners accomplish learning goals. • ***A two-level hinting*** model is used. • ***Adaptive and personalized*** pedagogy is provided. • The question selector model and ***algorithms*** are design and implemented. • ***Diverse media*** is provided for lessons and quizzes explanation.
System Implementation Aspect		• Shikshak tutor is a web-based tutoring system.	• It is used to teach SQL and a standalone system. • Use LISP • Later it is converted in SQLT-Web. • SQLT-Web is developed using the CL-HTTP server.	• AG_TUTOR is coded using Java net beans IDE 7.0, ODBC API & unlaces API • SQL, and Microsoft Access for a knowledge base.	• SeisTutor is coded using C# .net framework and C# fuzzy library. • Data storage is through the MS Access database running on a Windows platform. • Standalone offline application is compatible with Window platform.
Evaluation Aspect		**Experimental Setup:** • 33 students • Age: 12-16 years • Prior Knowledge: No • Learner Type: Students	**Experimental Setup:** • 79 students • Age: Details not available • Prior Knowledge: No • Learner Type: Students	**Experimental Setup:** • No details available.	**Experimental Setup:** • 53 students • Age: 17- 40 years • Prior Knowledge: No • Leaner Type: students, teachers, industry professionals.

		Empirical Evaluation: • **No** technique is used. **Evaluation of Learner:** • Performance is calculated and compared with classroom teaching. • Only ***comprehension-ability or problem-solving skills*** are evaluated. • No system evaluation	**Empirical Evaluation:** • Two groups are created. • Control group and experimental group. • Pretest and Post-test scores are used for both groups. • ***Mean***, ***standard deviation*** and ***t-test*** is used for evaluation • A user questionnaire is used. • ***Student's feedback*** is considered.	**Empirical Evaluation:** • **No** statistical method is used **Empirical Evaluation:** • No information is available.	**Empirical Evaluation:** • ***ANOVA*** technique and F Test is used. **Two levels of evaluation** • Evaluation of learners. • Evaluation of *'SeisTutor'* . **Evaluation of 'Learner'** • ***Pre and Posttest*** performance is considered. • ***Learning Gain*** is calculated. **Evaluation of 'SeisTutor'** • ***Learner Feedback Questionnaire (LFQ)*** is used • The system is evaluated using parameters i.e. ***System Effectiveness, Adaptability, Personalization, System Support, and Ease-to-use.***

2.7 SUMMARY

This chapter has explored the work in the field of ITS /E-learning System/ Hypermedia System for several domains. The various component of ITS architecture: Domain Model, Learner Model, Tutoring Model, and Learner Interface Model have been discussed. The Learner Model that is a crucial component of the ITS has been explored in detail. Subsequently, learner modeling techniques and their comparison in use in various systems (ITS/Adaptive/E-learning) have been discussed in terms of providing the adaptivity and personalization. Additionally, learner features such as domain competency level, cognitive, meta-cognitive, and learning style have been discussed. Also, the comparison of different learner characteristics in use in various systems (ITS/Adaptive/E-learning) has been discussed. The learning styles characteristic of learner, learning style models, and their usage in ITS is also discussed.

The following chapter, the learner model design along with their sub-models: Learner Characteristics Model, Leaner Classification Model, and Learner Adaptation Model will be discussed. Subsequently, the overview of research work, design, and development of components of ITS will be discussed.

CHAPTER 3: LEARNER MODEL DESIGN AND METHODOLOGY

This chapter introduces the detailed design of learner model, its components and flow of the sub modules of learner model, which incorporates learner characteristics model, the learner classification model, and the learner adaptation model. Also, the design of the tutoring model is discussed which incorporates Administrator Model, Tutoring Strategies Model, Pre-learning Procedure Model, Lesson Model, Quiz and Hint Models along with their sub-modules.

3.1 LEARNER/USER/STUDENT MODEL

The learner model also termed as a student model or user model that contains techniques for understanding what the learner does and doesn't have the foggiest idea. This model commonly portrays student attributes or boundaries, for example, earlier information, learning style, learner activity records, and psychological style that support the adaptation and personalization (Graf, Lin, and Kinshuk, 2008). The model doesn't only embodies the general data about the learners however can likewise be founded on tracking and logging learner actions inside the framework. Hence, the data in the model originates from evaluations of learners and joined with dynamic characteristics based on behavior and action performed by the learner.

The design and development of learner models takes a key role in the forthcoming web education system to make it adaptable. The reason for learner models is to drive personalization dependent on the learner and learning attributes that are considered significant for the learning procedure, for example, psychological, emotional, and behavioral. According to Brusilovsky & Millan (2007), to achieve adaptivity, the tutoring system ought to be educated about the individual qualities of the learners, and known as the “key to individualizing the adaptive instructions” (Millan, et. al., 2010). The learner model is proposed to recognize the individual attributes of a learner that causes the mentoring framework to offer the customized tutoring strategy to the learners. In the tutoring system, learner modeling is taking place using the learning style and competency level of the learner to make it adaptive. The proposed learner model design is made out of three components,

- *Learner Characteristics Model*- defines the characteristics of the learner.
- *Learner Classification Model*- categorize the learners into groups based on his/her background or attributes/characteristics.
- *Learner Adaptation Model*- learner diagnosis, assessment, present adaptive and personalized learning material.

The following Figure 3.1 represents the architectural framework of the proposed learner model which is one of the key components of the adaptive intelligent tutoring system. The proposed learner model is incorporated with three sub-modules: Learner Characteristics Model, Learner Classification Model, and Learner Adaptation Model in order to enrich the adaptation and personalization are discussed.

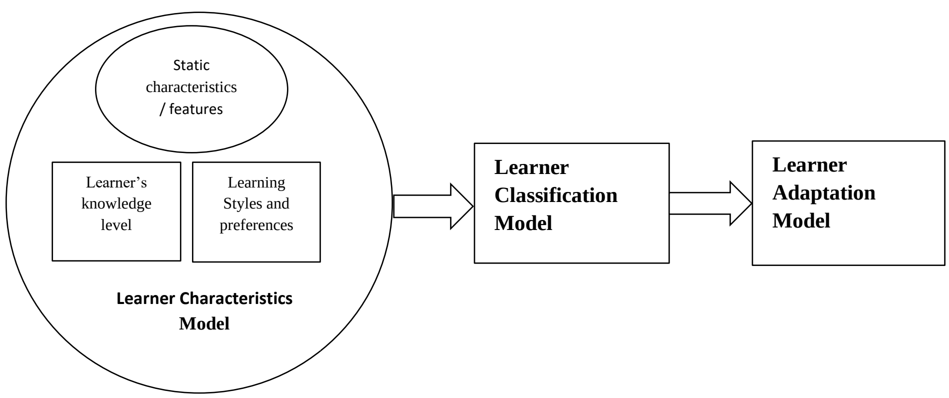


Figure 3.1 – Architecture of Proposed Learner Model

It is important to focus on the learner model in the development of an adaptive tutoring framework in order to provide personalize learning material. The idea of the proposed learner model is to offer a comfortable learning environment that is completely centered around student-driven. It is proposed to lead thorough a critical assessment of learner's characteristics, for example, competency level also termed as the knowledge level of a learner, learning style, and preferences. These identified characteristics are further classified into two-three sub characteristics that could be used by the learner classification model. From that point, a learner adoption model will be structured that fuses learner groups its information and uses it to build up an adaptive model to make the learning content adaptable to the learner. It is suggested that the learning material offered to the student has prone to be firmly adjusted to the student.

3.2 COMPONENTS OF LEARNER MODEL AND METHODOLOGY

3.2.1 Learner Characteristics Model

The learner characteristics model stores the features or attributes of the learner. The selection of learner characteristics is a complex and difficult process in the development of the learner model for the implementation of adaptivity and personalization. The adaptation and personalization could be embedded through consideration of learner characteristics Essalmi et al. (2009). According to Jeremic, Jovanovic, and Gasevic (2012), learner characteristics are arranged as static and dynamic attributes. Static attributes, for example, learner name, age, email id, and so forth and keep on unaltered all through the learning meeting and are set before the mentoring meeting begins. Dynamic attributes are not fixed and change based on learners' actions during learning sessions. They are accumulated and consistently refreshed based on student's activities or collaboration with the framework.

A critical investigation and study have been conducted on web-based tutoring systems. Numerous learner characteristics have used in literature based on their requirement and suitability in learning conditions. The current work is limited to learner characteristics such as learner prior knowledge level, learning style, and preferences. The proposed learner characteristics model composed of these learner features and used by the classification model to categorized into the groups.

The following Figure 3.2 represents the methodology of the learner model along with its subcomponents.

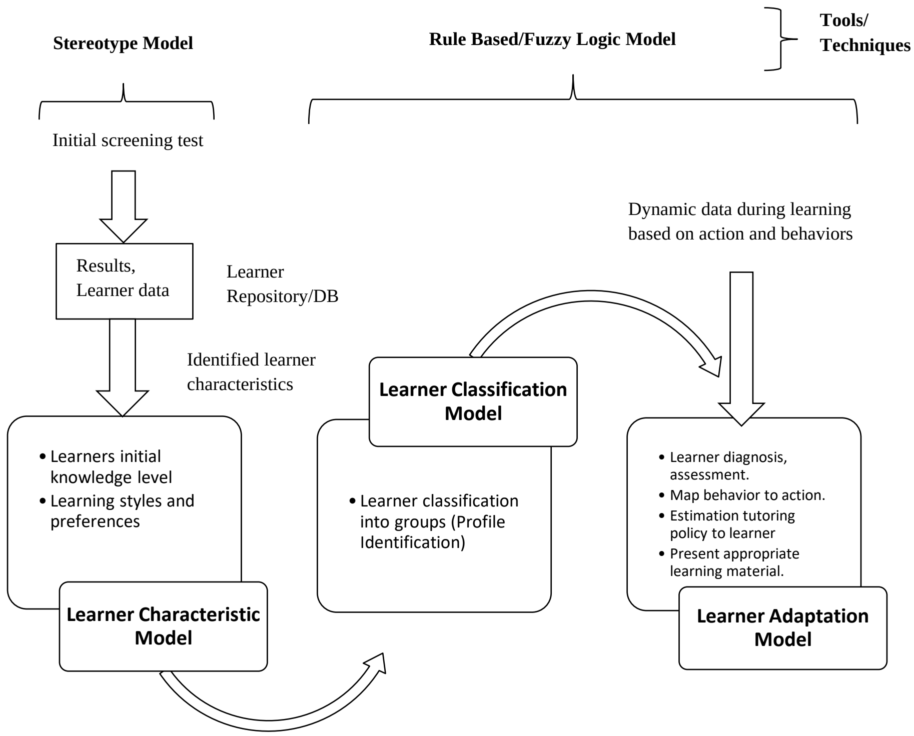


Figure 3.2 – Methodology: Proposed Learner Model and its Sub Components

The learner characteristics model works on the pre tutoring phase to gather the initial learner data. However, every individual has different and has different characteristics. Thus to give appropriate learning content and to understand learners, every learner is made to take an underlying screening test. The initial screening test is used to know the learner's prior knowledge about a particular subject domain. Thus, the score of every student is recorded, scaled, and standardized for consistency and stored in the learner characteristics model. The performance of each learner is saved in the repositories and later can be retrieved for further analysis purposes.

Penetrating down the recognized student attributes, explicit sub-attributes will be distinguished to demonstrate the student for giving flexibility in ITS. Different devices and procedures are proposed to be taken up to demonstrate these student attributes, as demonstrated as follows (Jeremic, Jovanovic, and Gasevic, 2012).

- Static characteristics implemented using Stereotypes Model
- Dynamic features implemented using Fuzzy Rule Based Approach

The data collected during pre-tutoring phase saved in the learner characteristics model and can be used by the classification model for further analysis.

3.2.2 Learner Classification Model

The learner classification model is used to classify the learners into groups according to their prior knowledge, initial learning style and preferences. The data received from the learner characteristics model worked as an input for the learner classification model. The combination of these individuals' characteristics placed in the classification model to provide the adaptive and personalized learning environments. The classification model is implemented using the fuzzy rule based techniques has discussed in next Section 4. The goal is to build up student's groups, which can be apportioned to a particular student, according to student's information and foundation investigation.

3.2.3 Learner Adaptation Model

The output of the classification model has given as an input to the adoption model. The adoption model understands learner preferences and accordingly offers the best-suited learning contents helping with managing every student's learning pace (Chrysafiadi and Virvou, 2012). This model works on the recording of learner actions, activities, and behavior during ongoing sessions. The recording of the state of a learner and map the action to the behavior is not black and white paper. The accurate evaluation and diagnosis of learners is a very difficult and complex process. Therefore, the accurate assessment of the learner is has been implemented using the fuzzy rule-based approach.

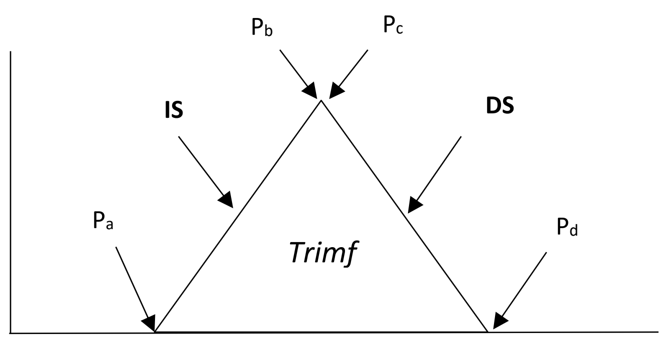
3.3 INCORPORATION OF RULE BASED FUZZY SYSTEM IN LEARNER MODEL

Learning is a complex and a continuous process and isn't exact to state that the domain concept is learned or not learned. Estimating the progress and accomplishment of learners is an arduous process, so, it is necessary the advancement of ITS. The Learners state of competency level has many variance, also have a different learning style, a different way of learning, and a different background (Jeremic et al., 2012). Therefore, the main challenge is that *"one shoe can't fit all",* so, why the *''same tutoring strategy for all"?* Therefore, the learner's competency level is not a variable that takes a constant value, it deals with lots of uncertainty and human subjectivity. In this manner, we introduced the fuzzy logic approach to handle the uncertainty and human subjectivity that is a rule-based technique and is a soft computing approach of Artificial Intelligence (AI). Fuzzy logic is used since it provides the human-like instructions to the learner (Drigas, Argyri, & Vrettaros, 2009) and helps to guides the actual learning path in the tutoring framework to make it adaptable.

3.3.1 Fuzzy Rules Design

A fuzzy membership function represented as *f(x)* has been formulated in the current work, where fuzzy function *f(x)* is denoted using the number range *f(x)* -> [0.0, 10.0]. The function *f(x)* represented by the four main points P_a, P_b, P_c, P_d and the *trimf* fuzzy membership function has been used. Figure 3.3 presents the diverse structures of the fuzzy function *f(x)* and *f(x)* is represented in the following Equation 3.1. Table 3.3 represents the description of fuzzy points for the triangular function (trimf).

$$f(x) = \left\{ \begin{array}{ll} \dfrac{X - P_a}{P_b - P_a} & \textit{For Increasing Section (IS)} \\ \dfrac{P_b - X}{P_d - P_c} & \textit{For Decreasing Section (DS)} \end{array} \right\} \qquad \textbf{\textit{Equation 3.1}}$$



IS – Increasing Section, DS – Decreasing Section

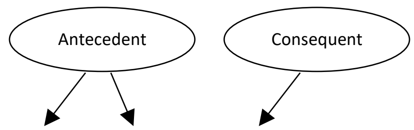
Figure – 3.3 General form of Fuzzy Membership Function of IS and DS for Triangular Function

Table 3.1 presents the description of fuzzy points for the triangular function (trimf).

Table 3.1 – Description of fuzzy points for triangular function

S.N	Feature	Description
1.	Function type	Define function type i.e. triangular
2.	P_a	Beginning point of IS part
3.	P_b	Finishing point of IS part
4.	P_c	Beginning point of DS part
5.	P_d	Finishing point of DS part

The fuzzy inference rules are based on Mamdani Fuzzy Approach since it is effectively utilized as a part of different ITSs (Mamdani and Assilian). The fuzzy rules in the form of *if-else* are used to figure the conditional statement which consists of antecedent and consequent part of fuzzy rules. The following has the general structure of the fuzzy rules



Basic Rule for i: IF l_1 and l_2 THEN l_3

The basic structure of the fuzzy rules is describe above, where l_1 and l_2 is called as linguistic characteristics work as an inputs in fuzzy rules, and l_3 is linguistic characteristics works as an output. The fuzzy is the process to formulate the logic from input to an outputs and follow the IFTHEN patterns. In the fuzzy rules, the IF part is identified as Antecedent and THEN-part is identified as the Consequent of the fuzzy membership function.

3.3.2 Score Normalization

The pre tutoring phase is used to collect the initial score of each learner from characteristics model. The learner classification parameters (DKT, LST) of each learner has been used to normalize to adjust the data for equal distribution. The Min-Max techniques is used for score normalization and it is most popular technique to normalize data. The Min-Max normalization techniques converts the value from X to Y that fits in the range [A, B]. The formula for score normalization is defined below, where

A is the lowest range; B is the highest range. In our case [A, B] is [0, 10];

$$Y = \left(\frac{\text{A – Lowest value of A}}{\text{Highest value of A – Lowest value of A}} \right) * (B-A) + A$$

This techniques of normalization provides the linear transformation of the learner data and fits the entire data in the range of [0-10]. This has done because the range uniformity of score is maintained.

3.4 LEARNER MODEL DESIGN

3.4.1 Learner Characteristics Model Design

There are two main characteristics of learner i.e. learner knowledge level and learning style considered in this research work. Both characteristics utilized to initiate the tutoring session. To initialize the tutoring sessions, two pre-tutoring test was conducted, first, Domain Knowledge Test (DKT), it is offered to learner to know his/her competency level and second, Learning Style Test (LST), which is offered to learner to distinguish the initial leaners learning style. These pre-tutoring tests are compulsory for learners who wish to use the tutoring system. Figure 3.4 represents the flow diagram of learner characteristics model.

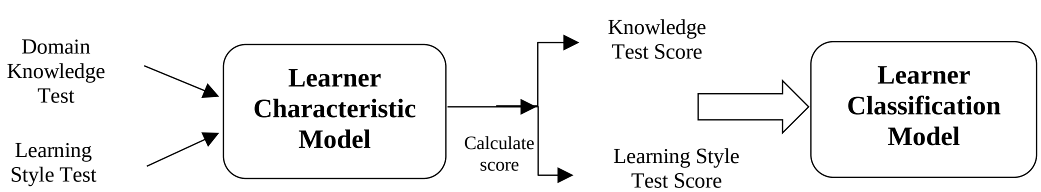


Figure 3.4 - Flow Diagram of Learner Characteristics Model

3.4.1.1 Learner Level

Learner Level (LL) is identified through the Domain Knowledge Test (DKT). The subject matter of Seismic Data Interpretation (SDI) has been identified for delivery through the proposed tutoring system. The DKT includes twenty questions solicited from the domain experts of field of SDI. This is the preliminary test used to ascertain elementary knowledge of the domain, to adjudge the initial competency level of the learner. The learners are classified under three Learning Levels (LL) such as Beginner (BEG), Intermediate (INT), or Expert (EXP) based on the score obtained in DKT (Grubišić, A., Stankov, S., & Žitko, B. 2013; Tsiriga, V., & Virvou, M., 2002; Tsiriga, V., & Virvou, M., 2003). Thus, initially, the learner is allocated any of the three stereotypes based on his/her performance of the pre tutoring test i.e. DKT.

To accomplish these learner stereotypes, a function *f(LL)* is formulated in this work, where *f(LL): f(LL)* -> [0.0, 10.0]. The function *f(LL)* represented through three main knowledge level stereotypes i.e. LL_{Level1}, LL_{Level2}, and LL_{Level3}. The different forms of *f(LL)* is shown below.

1. $LL_{Level1=}$ {0.0 <= *f(LL) < 3.5* }, score falling in this range is indicative of learner competency mapped at Level-1.
2. $LL_{Level2=}$ {3.5 <= *f(LL) < 7.0* }, score falling in this range is indicative of learner competency mapped at Level-2.
3. $LL_{Level3=}$ {7.0 <= *f(LL) <= 10.0* }, score falling in this range is indicative of learner competency mapped at Level-3.

The definition of the function *f(LL)* and the range defined previously helps us to define the stereotypes of the learner based on his/her domain knowledge. The stereotypes of learner are assigned as follows.

1. A learner is considered as *Beginner (BEG)* if allotted $LL_{Level1.}$
2. A learner is considered as *Intermediate (INT)* if allotted $LL_{Level2.}$
3. A learner is considered as *Expert (EXP)* if allotted $LL_{Level3.}$

The following Figure 3.5 represents the flow of the DKT.

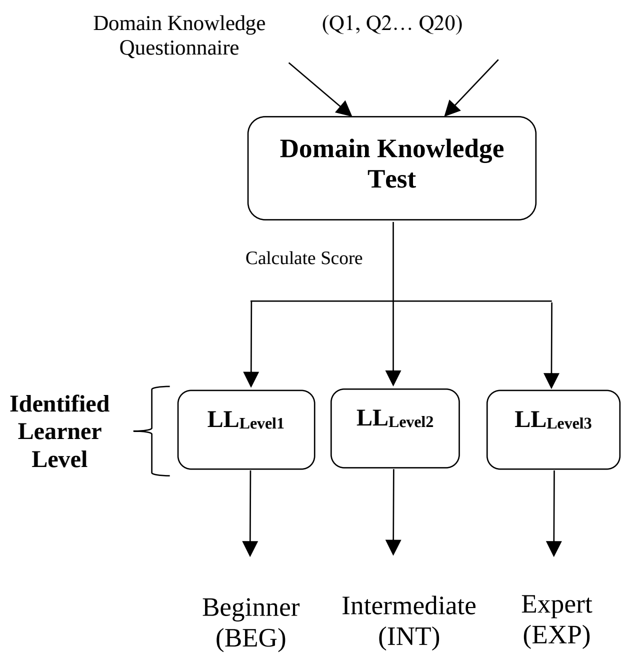


Figure 3.5 - Flow of Domain Knowledge Test (DKT)

3.4.1.2 Learning Style Test (LST)

I^2A^2 learning style model has been referred for the identification of learning style of learner. The Learning Style Question Pool (LSQP) includes eighteen enquiries and each has the four responses. Each responses belong to any one of the learning style dimensions i.e. imagistic, intuitive, acoustic, and active. The following Figure 3.6 represent the flow of the learning style model.

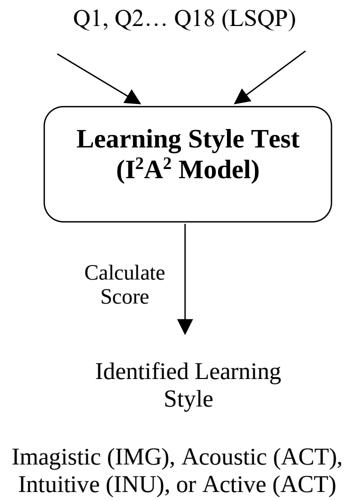


Figure 3.6 - Flow of Learning Style Test (LST)

3.4.2 Learner Classification Model Design

Learner stereotype modeling technique is used for designing the learner classification model and it is implemented using the fuzzy rule-based techniques. Fuzzy modeling techniques is used because majority of the human thinking process works similar to the fuzzy rules. According to Negnevitsky (2005), fuzzy rule-based system could be utilized to understand the human decision-making and the human common sense. It permits and covers ambiguous ideas and conquers restrictions, for example, the absence of data (Turksen, 2005).

According to Wang et. al., (2007), the objective to develop the learner classification model is to emulate the knowledge of teacher's in assessing the learners learning and motivation towards the learning procedure. The benefit of utilizing various fuzzy techniques is that it enables the system to utilize results of the fuzzy system exclusively or in blend with each other. The learner classification model attempts the two-classification parameters: DKT and LST. The flow of the learner classification models is shown in Figure 3.7.

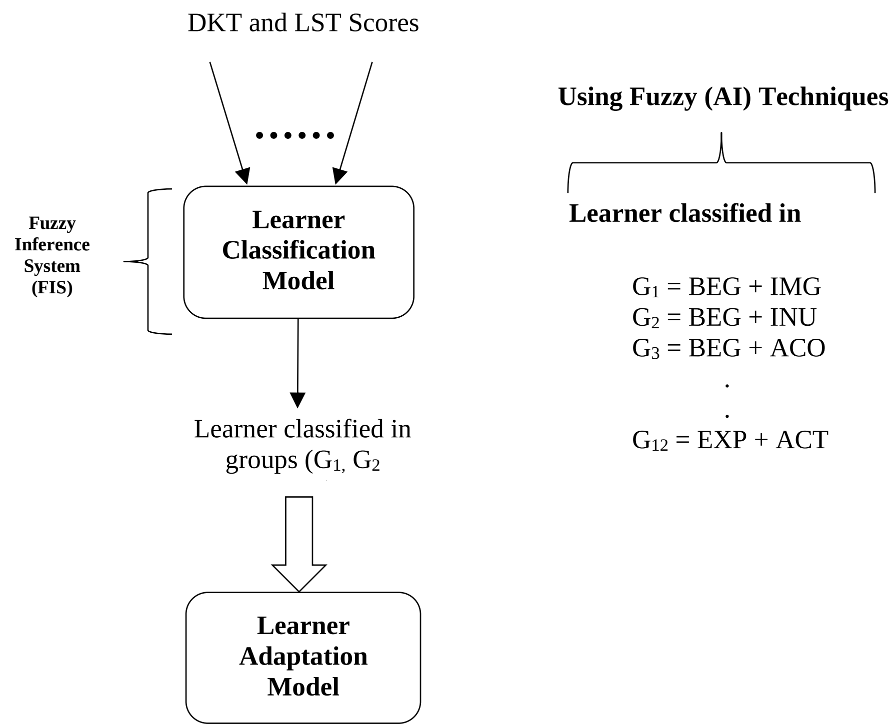


Figure 3.7 - Flow Diagram of Learner Classification Model

3.4.2.1 Fuzzy Rules Design for Learner Profile (LP) Identification

Learner profile is the combination of Domain Knowledge Test (DKT) and Learning Style Test (LST). Thus, in order to classify the learner, five input parameters are used such as Learner Level (LL), Imagistic (IMG), Intuitive (INU), Acoustic (ACO), and Active (ACT) are known as fuzzy input linguistics variables. The first input parameters LL prescribe three group of grades: "Beginner", "Intermediate", and "Expert", which are just like to "A", "A+", and "A++" in the academic grading system where "A++" is the highest and "A" is the lowest. Similarly, all the input linguistics parameters are classified in groups.

The output parameters LP prescribe twelve group of grades: ["G_1", "G_2"… "G_{12}"] and these learner profile classified groups are formulated in Table 3.2 below. Table 3.3 presents the range of fuzzy points of input and output linguistic variable for the learner classification model. Finally, five linguistic variables, each of having 3 classes, and 243(3^5) fuzzy rules are formulated. Table 3.3 presents the range of fuzzy points for input and output linguistic variables linguistic variable with descriptors.

Table 3.2 – Structure of learner's classified groups

Learner Level (LL)	**Learning Styles**	**Classified Groups**	
Beginner (BEG)	Imagistic (IMG)	BEG + IMG	G_1
	Intuitive (INU)	BEG + INU	G_2
	Acoustic (ACO)	BEG + ACO	G_3
	Active (ACT)	BEG + ACT	G_4
Intermediate (INT)	Imagistic (IMG)	INT + IMG	G_5
	Intuitive (INT)	INT + INU	G_6
	Acoustic (ACO)	INT + ACO	G_7
	Active (ACT)	INT + ACT	G_8
Expert(EXP)	Imagistic (IMG)	EXP + IMG	G_9
	Intuitive (INT)	EXP + INU	G_{10}
	Acoustic (ACO)	EXP + ACO	G_{11}
	Active (ACT)	EXP + ACT	G_{12}

Table 3.3 – The range of fuzzy points for input and output linguistic variables

S.N	Linguistic Variable	Descriptor	P_a	P_b	P_c	P_d
1.	Learner Level (LL)	Beginner	-3.5	0	0	3.5
2.		Intermediate	3	5	5	7
3.		Expert	6	8	8	10
4.	Imagistic	Few	-4	0	0	4
5.		Medium	3	5	5	8
6.		Large	7	10	10	12
7.	Intuitive	Small	-4	0	0	4
8.		Normal	3	5	5	8
9.		Long	7	10	10	12
10.	Acoustic	Short	-4	0	0	4
11.		Wide	3	5	5	8
12.		VeryWide	7	10	10	12
13.	Active	Low	-4	0	0	4
14.		Upper	3	5	5	8
15.		High	7	10	10	12
16.	Learner Profile (LP)	G_1	0.0	0.8	0.8	1.6
17.		G_2	0.8	1.6	1.6	2.4
18.		G_3	1.6	2.4	2.4	3.2
19		G_4	2.4	3.2	3.2	4.0
20.		G_5	3.2	4.0	4.0	4.8
21.		G_6	4.0	4.8	4.8	5.6
22.		G_7	4.8	5.6	5.6	6.4
23.		G_8	5.6	6.4	6.4	7.2
24.		G_9	6.4	7.2	7.2	8.0
25.		G_{10}	7.2	8.0	8.0	8.8
26.		G_{11}	8.0	8.8	8.8	9.6
27.		G_{12}	8.8	9.6	9.6	10.0

Membership Function for Learner Level (LL)

The measurements of *LL* has three memberships' functions having the ranges. All the ranges will map to the following fuzzy memberships function

$$M_i(x) = \{\text{Beginner, Intermediate, Expert}\}$$

Table 3.4 represents the ranges of fuzzy points for linguistics variable – Learner Level (LL). Figure 3.8 represents general form of fuzzy membership function for LL

Table 3.4 – The range of fuzzy points for linguistics variable: Learner Level (LL)

S.N	Linguistics Variable	P_a	P_b, P_c	P_d
1.	Beginner	-3.5	0	3.5
2.	Intermediate	3.0	5.0	7.0
3.	Expert	6.0	8.0	10.0

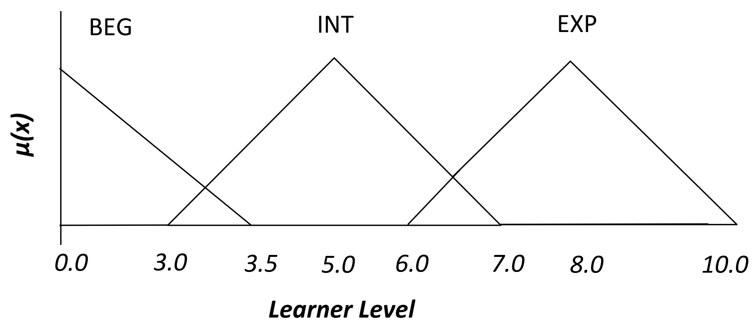


Figure 3.8 - General form of fuzzy membership function for LL

$$\mu_{BEG}(x) = \left\{ \frac{3.5 - X}{3.5} \quad , 0.0 <= x <= 3.5 \right\}$$

$$\mu_{INT}(x) = \left\{ \begin{array}{ll} \frac{X - 3.0}{2.0} & , 3.0 <= x <= 5.0 \\ \frac{7 - X}{2} & , 5.0 <= x <= 7.0 \end{array} \right\}$$

$$\mu_{EXP}(x) = \left\{ \begin{array}{ll} \frac{X - 6.0}{2.0} & , 6.0 <= x <= 8.0 \\ \frac{10.0 - X}{2.0} & , 8.0 <= x <= 10.0 \end{array} \right\}$$

__Membership function for Imagistic (IMG)__

The measurements of IMG has three memberships' functions having the ranges. All the ranges will map to the following fuzzy memberships function

$$M_i(x) = \{Few, Medium, Large\}$$

Table 3.5 represents the ranges of fuzzy points for linguistics variable – Imagistic (IMG). Figure 3.9 represents general form of fuzzy membership function for IMG.

Table 3.5 – The range of fuzzy points for linguistics variable: Imagistics (IMG)

S.N	Linguistics Variable	P_a	P_b, P_c	P_d
1.	Few	-4.0	0	4.0
2.	Medium	3.0	5.0	7.0
3.	Large	7.0	10.0	12.0

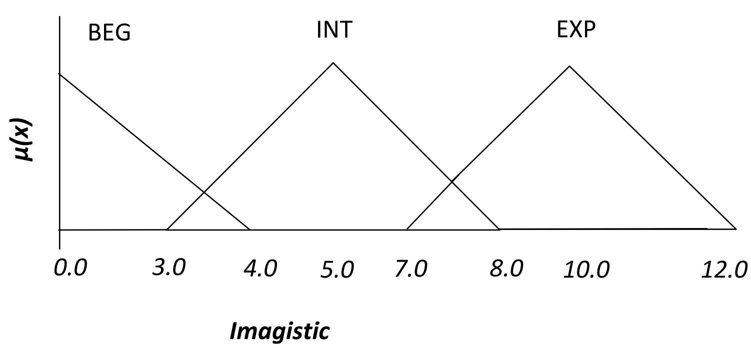


Figure 3.9 - General form of Fuzzy Membership Function for IMG

$$\mu_{BEG}(x) = \begin{cases} \dfrac{4.0 - X}{4.0} & , 0.0 <= x <= 4.0 \end{cases}$$

$$\mu_{INT}(x) = \begin{cases} \dfrac{X - 3.0}{2.0} & , 3.0 <= x <= 5.0 \\ \dfrac{7.0 - X}{2.0} & , 5.0 <= x <= 7.0 \end{cases}$$

$$\mu_{EXP}(x) = \begin{cases} \dfrac{X - 6.0}{2.0} & , 6.0 <= x <= 8.0 \\ \dfrac{10.0 - X}{2.0} & , 8.0 <= x <= 12.0 \end{cases}$$

Membership function for Intuitive (INU)

The measurements of INU has three memberships' functions having the ranges. All the ranges will map to the following fuzzy memberships function

$$M_i(x) = \{Small, Normal, Long\}$$

Table 3.6 represents the ranges of fuzzy points for linguistics variable – Intuitive (INU). Figure 3.10 represents general form of fuzzy membership function for INU.

Table 3.6 – The range of fuzzy points for linguistics variable: Intuitive (INU)

S.N	Linguistics Variable	P_a	P_b, P_c	P_d
1.	Small	-4.0	0	4.0
2.	Normal	3.0	5.0	7.0
3.	Long	7.0	10.0	12.0

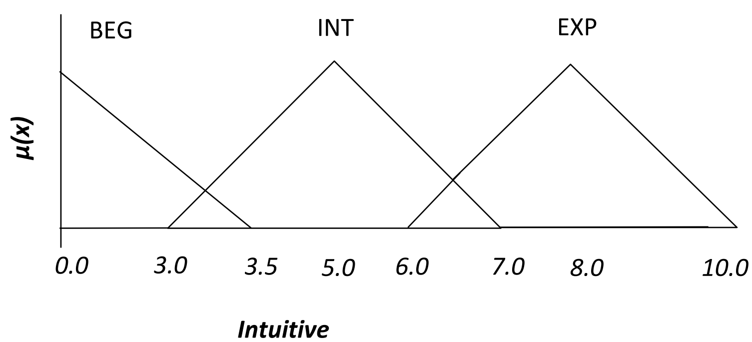


Figure 3.10 - General form of Fuzzy Membership Function for INT

$$\mu_{BEG}(x) = \left\{ \frac{3.5 - X}{3.5} \quad , 0.0 <= x <= 3.5 \right\}$$

$$\mu_{INT}(x) = \left\{ \begin{array}{ll} \frac{X - 3.0}{2.0} & , 3.0 <= x <= 5.0 \\ \frac{7 - X}{2} & , 5.0 <= x <= 7.0 \end{array} \right\}$$

$$\mu_{EXP}(x) = \left\{ \begin{array}{ll} \frac{X - 6.0}{2.0} & , 6.0 <= x <= 8.0 \\ \frac{10.0 - X}{2.0} & , 8.0 <= x <= 10.0 \end{array} \right\}$$

Membership function for Acoustic (ACO)

The measurements of ACO has three memberships' functions having the ranges. All the ranges will map to the following fuzzy memberships function

$$M_i = \{Short, Wide, VeryWide\}$$

Table 3.7 represents the ranges of fuzzy points for linguistics variable – Acoustic (ACO). Figure 3.11 represents general form of fuzzy membership function for ACO.

Table 3.7 – The range of fuzzy points for linguistics variable: Acoustic (ACO)

S.N	**Linguistics Variable**	P_a	P_b, P_c	P_d
1.	Short	-4.0	0	4.0
2.	Wide	3.0	5.0	7.0
3.	VeryWide	7.0	10.0	12.0

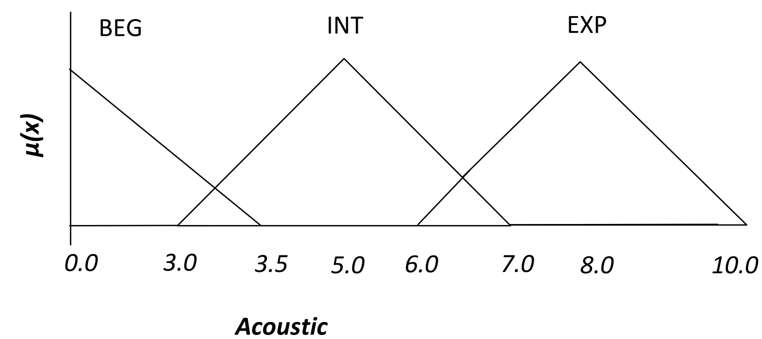


Figure 3.11 - General Form of Fuzzy Membership Function for ACO

$$\mu_{BEG}(x) = \left\{ \frac{3.5 - X}{3.5} \quad , 0.0 <= x <= 3.5 \right\}$$

$$\mu_{INT}(x) = \left\{ \begin{array}{ll} \dfrac{X - 3.0}{2.0} & , 3.0 <= x <= 5.0 \\ \dfrac{7 - X}{2} & , 5.0 <= x <= 7.0 \end{array} \right\}$$

$$\mu_{EXP}(x) = \left\{ \begin{array}{ll} \dfrac{X - 6.0}{2.0} & , 6.0 <= x <= 8.0 \\ \dfrac{10.0 - X}{2.0} & , 8.0 <= x <= 10.0 \end{array} \right\}$$

Membership function for Active (ACT)

The measurements of ACT has three memberships' functions memberships having the ranges. All the ranges will map to the following fuzzy memberships function

$$M_i = \{Low, Upper, High\}$$

Table 3.8 represents the ranges of fuzzy points for linguistics variable – Active (ACT). Figure 3.12 represents general form of fuzzy membership function for ACT.

Table 3.8 – The range of fuzzy points for linguistics variable: Active (ACT)

S.N	**Linguistics Variable**	**P_a**	**P_b, P_c**	**P_d**
1.	Low	-4.0	0	4.0
2.	Upper	3.0	5.0	7.0
3.	High	7.0	10.0	12.0

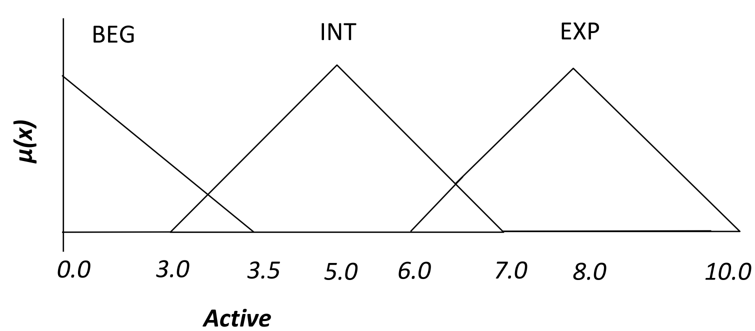


Figure 3.12 - General Form of Fuzzy Membership Function for ACT

$$\mu_{BEG}(x) = \left\{ \frac{3.5 - X}{3.5} \quad , 0.0 <= x <= 3.5 \right\}$$

$$\mu_{INT}(x) = \left\{ \begin{array}{ll} \frac{X - 3.0}{2.0} & , 3.0 <= x <= 5.0 \\ \frac{7 - X}{2} & , 5.0 <= x <= 7.0 \end{array} \right\}$$

$$\mu_{EXP}(x) = \left\{ \begin{array}{ll} \frac{X - 6.0}{2.0} & , 6.0 <= x <= 8.0 \\ \frac{10.0 - X}{2.0} & , 8.0 <= x <= 10.0 \end{array} \right\}$$

Membership function for Learner Profile (LP)

The measurements of LP has three memberships' functions memberships having the ranges. All the ranges will map to the following fuzzy memberships function

$$M_i(x) = \{G_1, G_2, G_3, G_4, G_5, G_6, G_7, G_8, G_9, G_{10}, G_{11}, G_{12}\}$$

Table 3.9 represents the ranges of fuzzy points for linguistics variable – Learner Profile (LP).

Table 3.9 – The range of fuzzy points for linguistics variable: Learner Profile (LP)

S.N	Linguistics Variable	P_a	P_b, P_c	P_d
1.	G_1	0.0	0.8	1.6
2.	G_2	0.8	1.6	2.4
3.	G_3	1.6	2.4	3.2
4.	G_4	2.4	3.2	4.0
5.	G_5	3.2	4.0	4.8
6.	G_6	4.0	4.8	5.6
7.	G_7	4.8	5.6	6.4
8.	G_8	5.6	6.4	7.2
9.	G_9	6.4	7.2	8.0
10.	G_{10}	7.2	8.0	8.8
11.	G_{11}	8.0	8.8	9.6
12.	G_{12}	8.8	9.6	10.0

Where G_1 represents the low level of competency and imagistic learning style. Similarly, the other groups are defined and formed. Based on the learner's group, the learning resources are developed and designed. The learner suited learning material has been offered to improve the knowledge level and content adaptivity. The following rectangle block defines the general form of the fuzzy rules and the learner classification algorithm is presented in the Algorithm-1 below.

IF Learner Level is *Excellent* **AND** Imagistic is *Few* **AND** Acoustic is *Normal* **AND** Intuitive is *Normal* **AND** Active is *Normal* **THEN** Learner Profile is G_1

Algorithm-1

LEARNERCLASSIFICATION (LL, IMG, INU, ACO, ACT, LP)

Retrieve the *Domain Knowledge Test (DKT)* scores from *“domainknowledgetestinfo”* file
Set *Learner Level (LL) = Domain Knowledge Test (DKT)* scores
Retrieve the *Learning Style Test (LST)* scores from *“learningstyletestinfo”* file
Set *Learning Style (LS) = Learning style dimensions (IMG, INU, ACO, ACT)* scores
IF *Learner Level (LL)* = ‘Beginner’ AND *Learning Style (LS)* is ‘IMG’
THEN *Learner Profile (LP)* = ‘G_1’
ENDIF
IF *Learner Level (LL)* = ‘Beginner’ AND *Learning Style* is ‘INU’
THEN *Learner Profile (LP)* = ‘G_2’
ENDIF
IF *Learner Level (LL)* = ‘Beginner’ AND *Learning Style* is ‘ACO’
THEN *Learner Profile (LP)* = ‘G_3’
ENDIF
IF *Learner Level (LL)* = ‘Beginner’ AND *Learning Style* is ‘ACT’
THEN *Learner Profile (LP)* = ‘G_4’
ENDIF
IF *Learner Level (LL)* = ‘Intermediate’ AND *Learning Style* is ‘IMG’
THEN *Learner Profile (LP)* = ‘G_5’
ENDIF
IF *Learner Level (LL)* = ‘Intermediate’ AND *Learning Style* is ‘INU’
THEN *Learner Profile (LP)* = ‘G_6’
ENDIF
IF *Learner Level (LL)* = ‘Intermediate’ AND *Learning Style* is ‘ACO’
THEN *Learner Profile (LP)* = ‘G_7’
ENDIF
IF *Learner Level (LL)* = ‘Intermediate’ AND *Learning Style* is ‘ACT’
THEN *Learner Profile (LP)* = ‘G_8’
ENDIF
IF *Learner Level (LL)* = ‘Expert’ AND *Learning Style* is ‘IMG’
THEN *Learner Profile (LP)* = ‘G_9’
ENDIF
IF *Learner Level (LL)* = ‘Expert’ AND *Learning Style* is ‘INU’
THEN *Learner Profile (LP)* = ‘G_{10}’
ENDIF
IF *Learner Level (LL)* = ‘Expert’ AND *Learning Style* is ‘ACO’
THEN *Learner Profile (LP)* = ‘G_{11}’
ENDIF
IF *Learner Level (LL)* = ‘Expert’ AND *Learning Style* is ‘ACT’
THEN *Learner Profile (LP)* = ‘G_{12}’
ENDIF

3.4.3 Learner Adaptation Model Design

The learner adaptation model evaluates and assesses the learner performance, and produce the learner report card in terms of their achievements. This model has the capability to interpret the learner's preference and ability to adapt the learning material. Figure 3.13 represents the flow of the learner adaptation model. The learner adaptation model includes the following parameters.

i. Learner Performance (LP)
ii. Degree of Engagement (DoE)
iii. Estimation of Tutoring Strategy (EoTS)

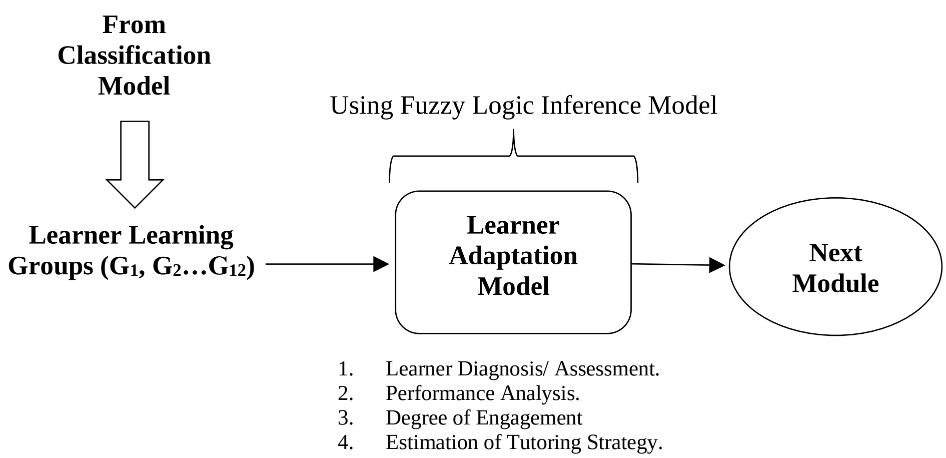


Figure 3.13 - Flow Diagram of Learner Adaptation Model

3.4.3.1 Fuzzy Rules Design for Learner Performance (LP)

The learner performance is calculated through the quizzes attempted, time taken during the learning sessions that provides improved results of the learning and the positive attitude toward the learning. The quizzes come in the series after the completion of the week wise course, each week contains three lessons. To calculate the overall performance of learner, three input performance parameters have used, First, Correct Response (CR), Second, Hint Taken (HT), and third, Time Taken (TT) were utilized, each of having four-membership function, 64 (4^3) rules will be formulated. Table 3.10 presents the range of fuzzy points for input and output linguistic variables linguistic variable with descriptors for Learner Performance.

i. Correct Responses (CR),

ii. Hint Taken (HT) and

iii. Time Taken (TT)

CR represents the number of correct questions attempted. HT represents the no of hint taken by the learner to attempt the quiz. Each question has one corresponding hint. TT represents the time period to complete the quiz.

Table 3.10 – The range of fuzzy points for input and output linguistic variable – Learner Performance

S.N	Linguistic Variable	Descriptor	P_a	P_b	P_c	P_d
1.	Correct Response (CR)	Poor	-4	0	0	4
2.		Good	3	5	5	7
3.		VeryGood	5	7	7	9
4		Excellent	8	10	10	12
5.	Hint Taken	Few	-3	0	0	3
6.		Medium	2	4	4	6
7.		Large	5	7	7	9
8.		VeryLarge	8	10	10	12
9.	Time Taken	Small	-3	0	0	3
10.		Normal	2	4	4	6
11.		Long	5	7	7	9
12.		Huge	8	10	10	12
13.	Learner Performance (LP)	Underachiever	-4	0	0	4
14.		Fine	3	5	5	7
15.		Strong	5	7	7	9
16.		Best	8	10	10	12

The Min-Max technique is utilized to normalize the performance parameters scores of each learner (refer Section 3.3.2).

Thus, in order to calculate the learner performance, three input linguistics parameters are used. The first input linguistic parameters (CR) recommend four group of grades:

“Excellent”, “VeryGood”, “Good”, “Poor” that are similar “A++”, ”A+”, “A”, and “A-” in the academic grading system, that means “A++” is the highest and “A-” is the lowest. Similarly, other input linguistic parameter (HT, TT) are classified in group of grades.

Membership function for Correct Response (CR)

The measurement of CR has four different membership function having the grade ranges and mapped with the function

$$M_i(x): M_i(x) \text{ belonged to } \{\text{Poor, Good, VeryGood, and Excellent}\}$$

Table 3.11 represents the ranges of fuzzy points for linguistics variable – Correct Response (CR). Figure 3.14 represents general form of fuzzy membership function for CR.

Table 3.11 – The range of fuzzy points for linguistics variable: Correct Response (CR)

S.N	**Linguistics Variable**	P_a	P_b, P_c	P_d
1.	Poor	-4.0	0.0	4.0
2.	Good	3.0	5.0	7.0
3.	VeryGood	5.0	7.0	9.0
4.	Excellent	8.0	10.0	12.0

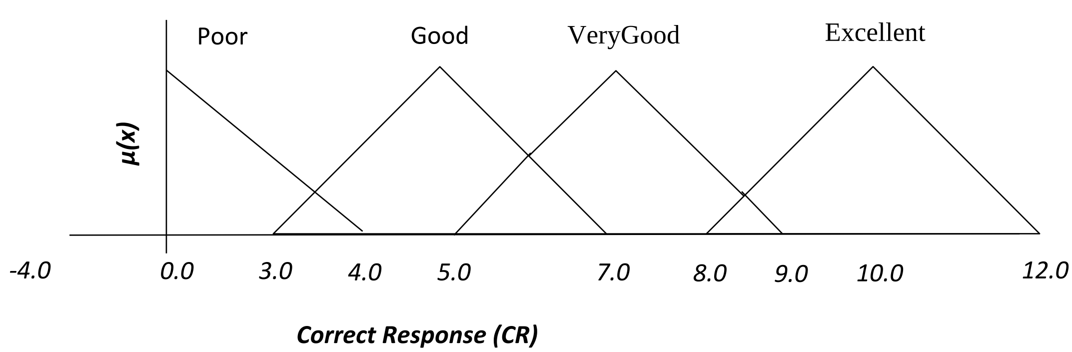


Figure 3.14 - General Form of Fuzzy Membership Function for CR

$$\mu_{POOR}(x) = \begin{cases} \dfrac{X + 4.0}{4.0}, & -4.0 <= x <= 0.0 \\ \dfrac{4.0 - X}{4.0}, & 0.0 <= x <= 4.0 \end{cases}$$

$$\mu_{GOOD}(x) \begin{cases} \dfrac{X - 3.0}{2.0}, & 3.0 <= x <= 5.0 \\ \dfrac{7.0 - X}{2.0}, & 5.0 <= x <= 7.0 \end{cases}$$

$$\mu_{VERYGOOD}(x) \begin{cases} \dfrac{X - 5.0}{2.0}, & 5.0 <= x <= 7.0 \\ \dfrac{9.0 - X}{2.0}, & 7.0 <= x <= 9.0 \end{cases}$$

$$\mu_{EXCELLENT}(x) \begin{cases} \dfrac{X - 8.0}{2.0}, & 8.0 <= x <= 10.0 \\ \dfrac{12.0 - X}{2.0}, & 10.0 <= x <= 12.0 \end{cases}$$

Membership function for Hint Taken (HT)

The measurement of HT has four different membership function having the grade ranges and mapped with the function

M_i (x): M_i (x) belonged to {Few, Medium, Large, and VeryLarge}

Table 3.12 represents the ranges of fuzzy points for linguistics variable – Hint Taken (HT). Figure 3.15 represents general form of fuzzy membership function for HT.

Table 3.12 – The range of fuzzy points for linguistics variable: Hint Taken (HT)

S.N	Linguistics Variable	P_a	P_b, P_c	P_d
1.	Few	-3.0	0.0	3.0
2.	Medium	2.0	4.0	6.0
3.	Large	5.0	7.0	9.0
4.	VeryLarge	8.0	10.0	12.0

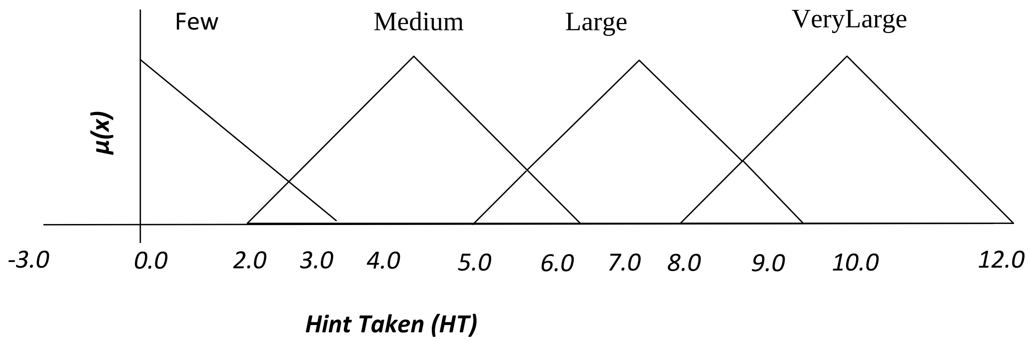


Figure 3.15 - General Form of Fuzzy Membership Function for HT

$$\mu_{FEW}(x) = \begin{cases} \dfrac{X + 3.0}{3.0}, & -3.0 <= x <= 0.0 \\ \dfrac{3.0 - X}{3.0}, & 0.0 <= x <= 3.0 \end{cases}$$

$$\mu_{MEDIUM}(x \begin{cases} \dfrac{X - 2.0}{2.0}, & 2.0 <= x <= 4.0 \\ \dfrac{6.0 - X}{2.0}, & 4.0 <= x <= 6.0 \end{cases}$$

$$\mu_{LARGE}(x) \begin{cases} \dfrac{X - 5.0}{2.0}, & 5.0 <= x <= 7.0 \\ \dfrac{9.0 - X}{2.0}, & 7.0 <= x <= 9.0 \end{cases}$$

$$\mu_{VERYLARGE}(x) \begin{cases} \dfrac{X - 8.0}{2.0}, & 8.0 <= x <= 10.0 \\ \dfrac{12.0 - X}{2.0}, & 10.0 <= x <= 12.0 \end{cases}$$

Membership function for TT

The measurement of TT has four different membership function having the grade ranges and mapped with the function

M_i (x): M_i (x) belonged to {Small, Normal, Long, and Huge}

Table 3.13 represents the ranges of fuzzy points for linguistics variable – Time Taken (TT). Figure 3.16 represents general form of fuzzy membership function for TT.

Table 3.13 – The range of fuzzy points for linguistics variable: Time Taken (TT)

S.N	Linguistics Variable	P_a	P_b, P_c	P_d
1.	Small	-3.0	0.0	3.0
2.	Normal	2.0	4.0	6.0
3.	Long	5.0	7.0	9.0
4.	Huge	8.0	10.0	12.0

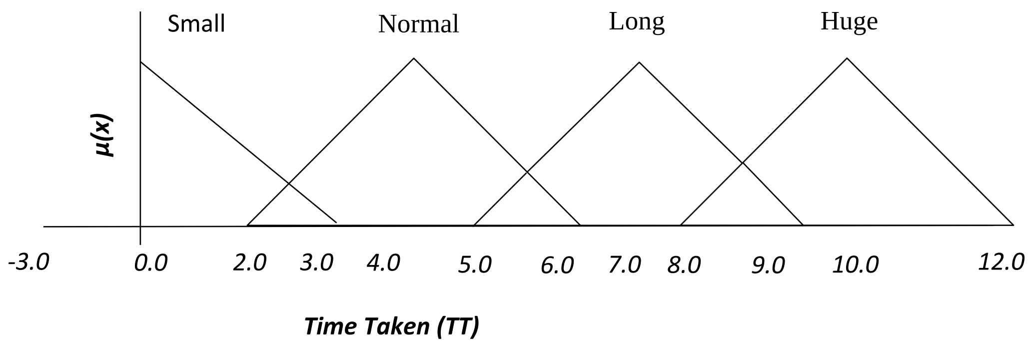


Figure 3.16 - General Form of Fuzzy Membership Function for TT

$$\mu_{SMALL}(x) \begin{cases} \dfrac{X + 3.0}{3.0}, & -3.0 <= x <= 0.0 \\ \dfrac{3.0 - X}{3.0}, & 0.0 <= x <= 3.0 \end{cases}$$

$$\mu_{NORMAL}(x) \begin{cases} \dfrac{X - 2.0}{2.0}, & 2.0 <= x <= 4.0 \\ \dfrac{6.0 - X}{2.0}, & 4.0 <= x <= 6.0 \end{cases}$$

$$\mu_{LONG}(x) \begin{cases} \dfrac{X - 5.0}{2.0}, & 5.0 <= x <= 7.0 \\ \dfrac{9.0 - X}{2.0}, & 7.0 <= x <= 9.0 \end{cases}$$

$$\mu_{HUGE}(x) = \begin{cases} \dfrac{X - 8.0}{2.0}, & 8.0 <= x <= 10.0 \\ \dfrac{12.0 - X}{2.0}, & 10.0 <= x <= 12.0 \end{cases}$$

Membership function for Learner Performance (LP)

The measurement of LP has four different membership function having the grade ranges and mapped with the function

M_i (x): M_i (x) belonged to {Underachiever, Fine, Strong, and Best}

Table 3.14 represents the ranges of fuzzy points for linguistics variable – Learner Performance (LP). Figure 3.17 represents general form of fuzzy membership function for LP.

Table 3.14 – The range of fuzzy points for linguistics variable: Learner Performance (LR)

S.N	Linguistics Variable	P_a	P_b, P_c	P_d
1.	Underachiever	-4.0	0.0	4.0
2.	Fine	3.0	5.0	7.0
3.	Strong	5.0	7.0	9.0
4.	Best	8.0	10.0	12.0

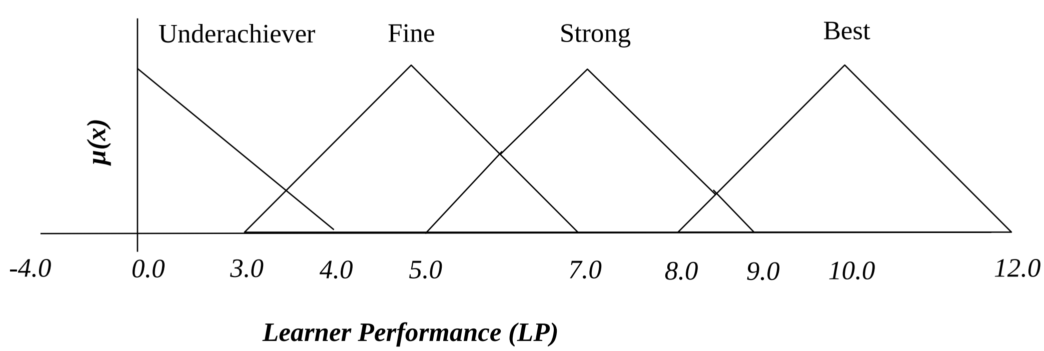


Figure 3.17 - General Form of Fuzzy Membership Function for LP

$$\mu_{UNDERACHIEVER}(x) = \left\{ \begin{array}{ll} \frac{X + 4.0}{4.0}, & -4.0 <= x <= 0.0 \\ \frac{4.0 - X}{4.0}, & 0.0 <= x <= 4.0 \end{array} \right\}$$

$$\mu_{FINE}(x) = \left\{ \begin{array}{ll} \frac{X - 3.0}{2.0}, & 3.0 <= x <= 5.0 \\ \frac{7.0 - X}{2.0}, & 5.0 <= x <= 7.0 \end{array} \right\}$$

$$\mu_{STRONG}(x) = \left\{ \begin{array}{ll} \frac{X - 5.0}{2.0}, & 5.0 <= x <= 7.0 \\ \frac{9.0 - X}{2.0}, & 7.0 <= x <= 9.0 \end{array} \right\}$$

$$\mu_{BEST}(x) = \left\{ \begin{array}{ll} \frac{X - 8.0}{2.0}, & 8.0 <= x <= 10.0 \\ \frac{12.0 - X}{2.0}, & 10.0 <= x <= 12.0 \end{array} \right\}$$

The “Best” class represents that the learner has good understanding in the subject domain of SDI and has the skills to accomplish whole learning assignment effectively. The “Strong” class represents that the learner has good understanding in the subject domain of SDI has the skills to finish most of the learning assignments. The “Fine” class represents the learner has elementary understanding in the subject domain of SDI to finish certain learning assignment effectively. The “Underachiever” class represents the learner has limited ability to understand in the subject domain of SDI to finish most learning assignments effectively.

IF-THEN rules have been utilized for the decision making. The commitment to each standard depends on the allotted esteem for the information boundaries (CR, HT, and TT), and the yield is the fuzzy sets that can be defuzzified later, and assign one values to the output parameter i.e. LP (Learner Performance). Considering all three fuzzy parameter and each of having four classes, 64 (4^3) unique standard rules and conditions have been formed. The formats of the typical fuzzy rules are shown below.

IF Correct Response is *Excellent* **AND** Hint Taken is *Few* **AND** Time Taken is *Normal* **THEN** Learner Performance is *Best*

3.4.3.2 Degree of Engagement (DoE)

The real time spent by the learner to accomplish any learning assignment or invested in the meaning full practices is known as DoE (Nash, 2005; Angelino *et al*. 2007). The DoE assume a significant role in the learning procedure and various experts suggest that students who are continuously busy with learning through ITSs will undoubtedly gain progress (Rishi and Govil, 2008).

3.4.3.3 Estimation of Tutoring Strategy (EoTS)

This module estimates the effectiveness of dynamically allocated tutoring strategy to the learner. The tutoring sessions are executed in a week-wise pattern. After every week, the checkpoint has been built into the system. At this checkpoint, we estimate the learner performance through evaluation of LP parameters (see Section 6.4.3.1). This assessment helps to test the adaptivity and personalization features of the system. If the learner performance has down with the system threshold value, then a trigger is generated automatically in the system. This trigger shows a message to the learner screen, which includes two options, first is, want to change the tutoring strategy, and second is, want to continue with tutoring strategy that is assigned? The tutoring process is paused immediately when this trigger is generated. The system suggests to the learner for changing the tutoring strategy if the performance of learner is down. This trigger is system generated and based on the LP parameter value but the full control to change the tutoring strategy is given to the learner.

At this trigger point, considering the case 1, if the learner clicks on "*change tutoring strategy*" option, then the new next appropriate tutoring strategy is assigned based on their profile. Now, the learner will get the learning material based on the new tutoring strategy. In this case, the learner can also revise the lesson that is already learned through the old tutoring strategy. Now considering next case i.e. case 2, if the learner clicks on the button "*to continue with the same tutoring strategy*" (current TS), then the tutoring will continue with the same strategy. As a result, we can say the system is enable to provide the personalized and adaptive tutoring strategy to the learner.

The used algorithm is presented below in Algorithm-2 and Figure 3.18 presents the procedure for changing the Tutoring Strategy (TS).

Algorithm-2:

IF *Learner's Fuzzy Performance Values (LFPV) < 5.0*
THEN *a message is triggered automatically with the choice "change TS" or "continue with the same TS"*
IF *learner select the choice "change TS"*
THEN *TS will change and new TS is assigned to learner based on learner profile*
IF *learner select the choice, "continue with the same TS"*
THEN *learner continue with the same TS*

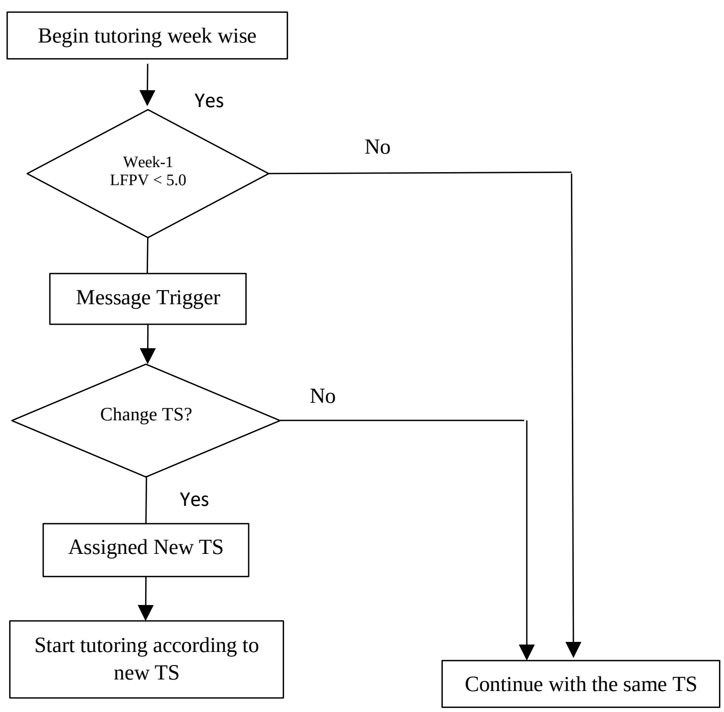


Figure 3.18 – Flow chart for changing Tutoring Strategy (TS)

Criteria for assigning new tutoring strategy

The new tutoring strategy is assigned based on the learning style scores calculated in Table 7.3 (see Section 7.4.1.1). As a result of learning style test, four scores are calculated based on the learning style dimensions: imagistic, intuitive, acoustic, and active. The second highest score is utilized for selecting the new tutoring strategy for the learner. The trigger is generated then only if the learner's fuzzy performance values (see Table 7.3 in Section 7.4.1.1) is down based to the following rule.

IF *Learner's Fuzzy Performance Values (LFPV)* < 5.0 **THEN** *Trigger is generated to change* the *Tutoring Strategy.*

3.5 TUTORING MODEL DESIGN

The tutoring model controls the behavior of the tutoring system through the multiple layers of models and its sub modules. Tutoring model incorporates all its submodules such as Administrator Model, Tutoring Strategies Model, Pre-learning Procedure Model, Lesson Model, Revision Model, Explanation Model, Quiz and Hint Model presented in Figure 3.19.

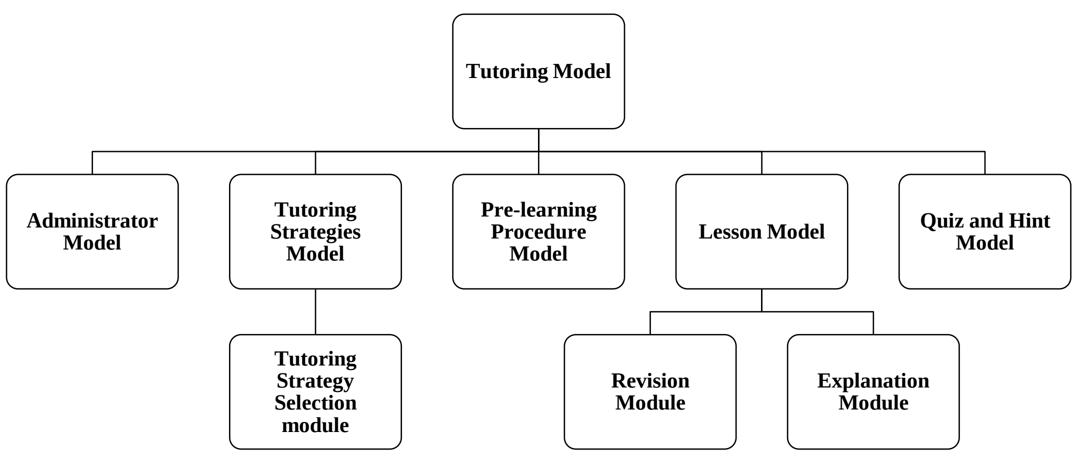


Figure 3.19 - Architecture of Tutoring Model

3.5.1 Administrator Model

This model is responsible for providing the prerequisites condition to the learner and the teacher in the ITS. The administrator model additionally controls the pre-learning stage of a learner, for example, enrollment with the system, the introduction of the pre-tutoring test and gathering the learner background data (name, email, gender, or age). At the time of account set up with a tutoring system, the student enters his/her own static data, for example, gender, age, or email. The pre-tutoring test is intended to evaluate the learner's background domain knowledge about the course he/she wants to study. The algorithms for registering the learner with ITS is presented in Algorithm-3.

Algorithm-3

IF the *learner* is New
THEN register as *new learner* AND get Learner ID
Save the registration information of learner in *"LearnerInfo"* file
ENDIF
IF learn *pre-requisites* for pre-tutoring tests *"Domain Knowledge Test"* AND *"Learning Style Test"*
THEN begin either *pre-tutoring tests*
ENDIF
ELSE read *pre-requisites* first.
ENDELSE
IF learner selects *"Domain Knowledge Test"*
THEN *"Domain Knowledge Test"* is presented
Save the score in the *"domainknowledgetestinfo"* file
ENDIF
IF learner selects *"Learning Style Test"*
THEN *"Learning Style Test"* is presented
Save the score in the *"learningstyletestinfo"* file
ENDIF
Get the learner score from *"domainknowledgetestinfo"* AND *"learningstyletestinfo"* file and profile is created and begin tutoring based on profile.

3.5.2 Tutoring Strategies Model

The tutoring strategies (TS) is defined as a pedagogy assigned to learner for tutoring. There are twelve TS and any one can be assigned to the learner based on his/her stereotypes.

Figure 3.20 represents the architecture of TS model and Algorithm-4 presents the procedure of Tutoring Strategy Model.

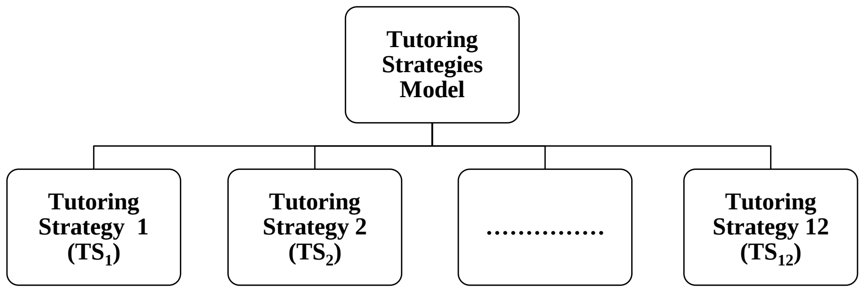


Figure 3.20 - Tutoring Strategies Model

Algorithm-4

TUTORING_STRATEGY (LP, TS)

IF *Learner Profile (LP) = 'G_1'*
THEN TS = 'TS_1'
IF *Learner Profile (LP) = 'G_2'*
THEN TS = 'TS_2'
IF *Learner Profile (LP) = 'G_3'*
THEN TS = 'TS_3'
IF *Learner Profile (LP) = 'G_4'*
THEN TS = 'TS_4'
IF *Learner Profile (LP) = 'G_5'*
THEN TS = 'TS_5'
IF *Learner Profile (LP) = 'G_6'*
THEN TS = 'TS_6'
IF *Learner Profile (LP) = 'G_7'*
THEN TS = 'TS_7'
IF *Learner Profile (LP) = 'G_8'*
THEN TS = 'TS_8'
IF *Learner Profile (LP) = 'G_9'*
THEN TS = 'TS_9'
IF *Learner Profile (LP) = 'G_{10}'*
THEN TS = 'TS_{10}'
IF *Learner Profile (LP) = 'G_{11}'*
THEN TS = 'TS_{11}'
IF *Learner Profile (LP) = 'G_{12}'*
THEN TS = 'TS_{12}'

3.5.2.1 Tutoring Strategy Selection Module

The tutoring strategy selection model select and sequence the exclusive tutoring strategy to the individual learner. The selection of the exclusive tutoring strategies is also the part of personalization scheme of the SeisTutor. The selection module search the repository/database to select an appropriate pedagogy to teach each topic to individual learner. Various types of tutoring methods were used to teach the same topic based on the learner's background. The system has the ability to interpret the learner's preferences and to provide the exclusive/personalized learning materials.

The basic approach used to select the tutoring strategy is the IF-THEN rule-based. The TS assigned using the IF-THEN rules formulated in the Table 3.15.

Table 3.15 – Procedure of tutoring strategy selection

	Classified Groups (Antecedent)		Tutoring Strategies (Consequent)
	G_1		TS_1
	G_2		TS_2
	G_3		TS_3
	G_4		TS_4
	G_5		TS_5
IF	G_6	**THEN**	TS_6
	G_7		TS_7
	G_8		TS_8
	G_9		TS_9
	G_{10}		TS_{10}
	G_{11}		TS_{11}
	G_{12}		TS_{12}

3.5.3 Pre-learning Procedure Model

The Learner must study the course pre-learning procedure, which is required to select the proper tutoring strategy or to begin the course for tutoring.

3.5.4 Lesson/Content Model

This model employs the tutoring strategy or content to be deliver to the learner and it gives the sequencing of course modules/structures. The entire course is classified in the four weeks, each week contains the three lessons, and each lesson contains the many topic. The lessons belongs to the SDI course. Lesson model covers rules in charge of sequencing of every lesson and its sub models, for example, revisions, explanation. Figure 3.21 presents the tree architecture of lesson model.

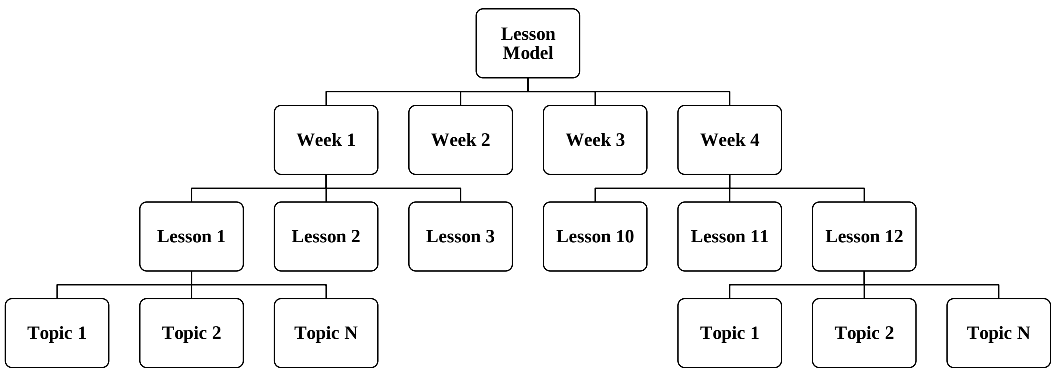


Figure 3.21 - Tree Structure of Lesson Model

3.5.4.1 Revision Module

The revision module gives intelligent learning materials and a few questions identify with the present lesson. The revision model gives the personalized analysis of the learner.

3.5.4.2 Explanation Module

This module gives review and direction to learners, in regards to his/her present and past communication/interaction by the tutoring system. The Explanation module has two styles of content explanations, first, lesson, second, quiz question mode. Initially, the lesson style gives a clarification and explanation of contents to the learner. After completion of the lesion, quiz is provided to assess the performance of learner.

3.5.5 Quiz and Hint Model

The assessment of the learner performance is based on the three parameters i.e. correct responses, number of hint taken, and time taken to complete the quiz questions. Each quiz contains five questions and each question have corresponding hint. Hints are based on the learner's on demand request for seeking the help to solve the questions. There is only one hint for each question and considered to assess the learner performance. Figure 3.22 presents the representations of quiz model.

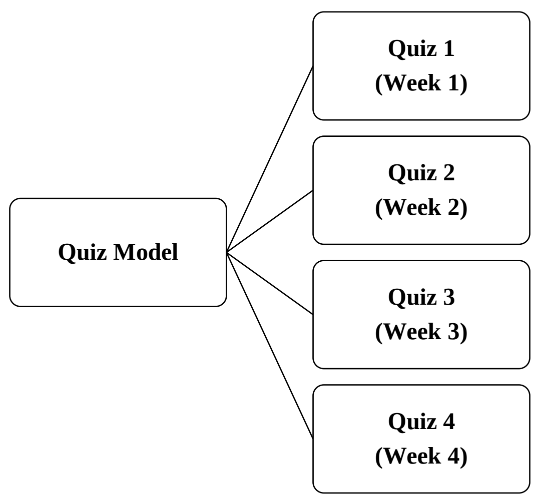


Figure 3.22 – Representation of Quiz Model

The learner must attempt the quizzes question after finishing committed lessons (i.e. revision and explanation) and before moving to the following lesson units (i.e. next week). The quiz model responsible for giving the questions and analysis of learner's responses in terms of learner performance. The appropriate responses to the questions influence the learner's grade/performance. Figure 3.23 presents the flow of the week wise quizzes.

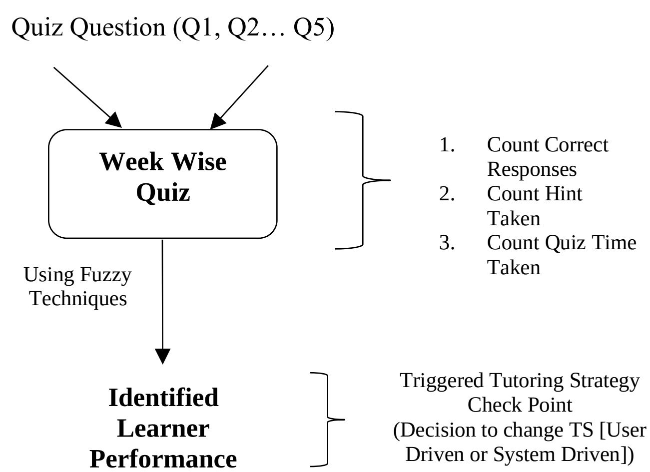


Figure 3.23- Flow Diagram of Week Wise Quiz

3.6 SUMMARY

The learner model depicted with its three sub models. The learner model and its sub models use the basic learner stereotypes and implemented through the fuzzy logic inferences, fuzzy membership function, and configurable flexible rules. It gives the benefit of providing different reasoning results that is utilized independently or in the mix with the other. Furthermore, the design of the tutoring model is discussed. The tutoring model controls the behavior of the tutoring systems through it sub models such as Administrator model, Tutoring model, Pre-learning procedure model, Lesson model, Quiz and Hint model, Revision model, and the Explanation Model. Each model is described by the IF THEN ELSE rules, figures, and the tables.

In the following chapter, the innovative I^2A^2 learning style model, its dimensions, and recommended pedagogy corresponding to the model will be discussed.

CHAPTER 4: PROPOSED I^2A^2 LEARNING STYLE MODEL

Based on the several limitations, criticisms, and challenges discussed in Section 2, proposing an innovative I^2A^2 learning style model that could assist with distinguishing the learning style of learner in order to make learning framework adaptive, effective and personalized. This model is developed as simple as compared to other existing in the literature and has an efficient approach to identify the learning style of learner.

4.1 NOVEL I^2A^2 LEARNING STYLE MODEL

I^2A^2 learning style model is an acronym of its four principal learning style dimensions such as Imagistic, Intuitive, Acoustic, and Active. Learners learn in multidimensional ways and individuals have different learning choices and strengths in regard to take in and process the information. In this sense, every learner has distinct learning styles. Some learner prefers to learn in the theoretical or in an abstract way like- through prototype model, abstract symbols, or concepts while others prefer an experimental or practical approach with some facts. Some learner prefers to take information visually or imagistically - using charts, figure, diagram, or images while others are comfortable with listening to the lectures, watching videos, and verbal description by someone. Some learners like to do the things first and then analyze the result later. Such type of learners actively participate to facing challenges and are dynamic in nature. Thus, there is diversity in the learning style of learners. In respect to that, we proposed an innovative learning style model.

Imagistic, Intuitive, Acoustic, and Active are termed as the four Learning Style Dimensions (LSD) of the proposed I^2A^2 model. The I^2A^2 model gives the score on every one of the four kinds of LSD. The Learners learning style inclinations extend from number1 (one) to every one of the 4(Four) learning measurements. A Learning Style Question Pool (LSQP) is designed for identifying the learning preferences of the learner. The LSQP is composed of the 18 questions/enquiries. In the I^2A^2 LSQP, every learner is asked eighteen inquiries and he or she needs to choose at least one or maximum four of the responses that facilitate his or her relation to predefined learning style inclinations. The I^2A^2 four learning style dimensions are shown in Figure 4.1 and will be discussed in the next below subsections.

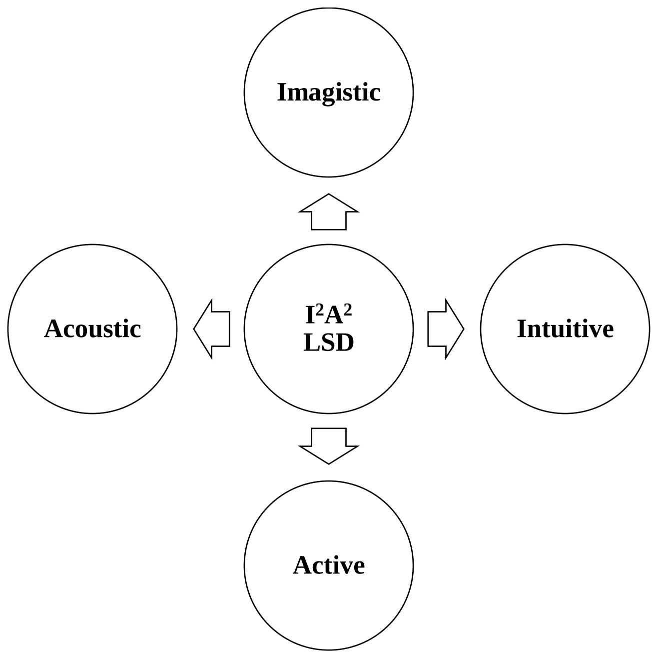


Figure 4.1 - I^2A^2 Learning Style Dimensions (LSD)

4.1.1 Imagistic Learner

Imagistic learner recalls information best what they have seen: charts, outlines, stream graphs, courses of events, movies, exhibitions. On the off chance that something is essentially said to them they will presumably overlook it. Imagistic learners need to visualize educator's non-verbal correspondence and relate with outward appearance to totally grasp the learning material. They are comfortable with classroom teaching and think in pictures and may benefit best from visual introductions including outlines, delineated reading materials, charts, utilization of intelligent whiteboards, and written notes.

4.1.2 Intuitive Learner

These learners favor learning materials in words and accentuation is set on content-based information and yield, for instance, perusing and writing in all structures. A learner who leans towards such methodology loves to work with power-point slide, internet, records, lexicons, and words. A critical difference with intuitive learner is, they are happier with studying written notes and material. Since words making an interpretation of them into what they speak to easily falls into place for intuitive learners.

4.1.3 Acoustic Learner

These learners learn best through verbal talk, trade of musings, conversing with individuals, and checking out what others have to state. Sound-related students decipher the key consequences of talk through checking out the voice tone, pitch, precision, and speed. These learners frequently take advantage of reading the text and notes tuning in to recorded notes, and data from writings. Acoustics learner gets the information through the group discussions, listening to some stories from other people, and interaction with people or explaining the things.

4.1.4 Active Learner

Active learners convert their knowledge into the form of experimental work and do not believe only in the theoretical concepts. These learners perceive the data through the mental process and update their knowledge over time into learning. Dynamic student remembers achieving something for the external world with the information—discussing it or explaining it or testing it some way or another. An "Active student" is somebody who feels greater with, or is better at dynamic experimentation. Active learners learn best through hands-on exercise or action-based learning to sit still for long stretches.

These learners do not much involve in the boring lecture or in the passive task, prefer to solve new challenges every time, and prefer to work in a group. Active learners believe in experimentation task. Active connotes that students accomplish something in class past just tuning in and watching, e.g., examining, addressing, contending, conceptualizing, or reflecting. Active students are the ones who assess the thoughts, outline furthermore, do the investigations, and eager to discover the solution to a problem that works- the coordinators, the chiefs. The summary of four LSD is presented in Table 4.1.

Table 4.1: Summary of four dimensions of I^2A^2 Learning Style Model

Imagistic	**Intuitive**	**Acoustic**	**Active**
Imagistic learners learn best what they have seen: charts, outlines, stream graphs, courses of events, movies, and exhibitions.	prefer to contemplate unique hypotheses and their hidden significance	May experience issues with written instructions ,comfortable with understanding of voice, easily diverted by clamors	Discuss with colleagues, to clarify doubts or test the learned material.
Psyche at times strays amid verbal exercises, Easily put off by visual diversions	Gains from written content and utilizes illustrations just as supplementary material.	Whispers to self while perusing, may murmur or sing while working,	In Open discussion forum, post material frequently to ask other, talk about, and clarify something.
Observes, instead of talks or acts; might be tranquil by nature, Memorizes by making mental pictures, Thinks in pictures,	Invest higher energy in content questions and lower time on illustrations.	Can recollect and frequently mirror discourse by getting musicality of the sentence,	Believe in self-assessment and assignment, real-time project and invest more energy in solving problems.
Feel verbal guidelines troublesome, remembers faces, relies on early introductions	Innovative and like difficulties	May evaluate individuals by the sound of their voice, Enjoys music and the hints of words	Spends very less time to study examples, since they favor doing the task and accomplishing themselves instead of waiting for other person solving the problem.
Likes drawing, may have great penmanship, Enjoys utilizing shading, Notices subtle elements, Often a snappy scholar	Give answer/inquiries concerning producing a unique solution, which requires the comprehension of fundamental hypotheses and ideas.		Active students don't learn much in circumstances that require them to be inactive, Avoid reading Like to take care of issues by physically working through them
Go in the depth of topic details, sometime may be good thinker			May require time to think (i.e. process the activities included), Will attempt always new things – likes to get included

4.2 THE I^2A^2 LEARNING STYLE QUESTION POOL (LSQP)

The I^2A^2 Learning Style Question Pool (LSQP) is an 18 (eighteen) questions pool designed to assess the preferences of the 4 LSD (Imagistic, Intuitive, Acoustic, and Active) of the I^2A^2 model. When someone attempts the I^2A^2 LSQP, a dynamically profile is created immediately with scores of all four LSD, and briefly explaining the meanings of each LSD. The process of dynamically profile creation is presented in Figure 3.2. The I^2A^2 LSQP is available for individuals for identifying their learning style preferences, educators or students, who wish to use in homeroom educating or for research reason. Every LSD is associated with 18 questions, and each option (a, b, c, or d) is corresponding to one or other LSD. Each option belongs to any one of the learning style dimensions and accordingly score for the same is assigned. I^2A^2 LSQP is presented in Appendix A at the end of the thesis.

4.3 LEARNING STYLES (LS) AND RECOMMENDED PEDAGOGY STYLE (RPS)

A learning style is characterized as an individual's favored method for learning. At the point when an educator's teaching style coordinates with learners learning style, the learner is more likely to encounter fulfillment and uplifted state of mind of identifying. Notwithstanding, there is presently no consensus concerning what degree of identifying styles really influence a learner's capacity to do well. There may be different ways to deal with learning styles and pedagogy style. The first way is to identify the learners learning style and then adjust pedagogy to an individual's needs, knowledge, and inclinations. The second way is to distinguish a learner's favored style and after that plan to design pedagogy strategies toward the inverse inclination with a specific end goal to fortify less favored style. The third way does not endeavor to recognize a learner's style, yet rather utilizes diverse tutoring strategies and learning object in the general learning background. This approach speaks to an endeavor to achieve all students and expects that each learner will discover something in the learning. Table 4.2 presents the recommended pedagogy style corresponding to each learning dimension of I^2A^2 learning style model.

Table 4.2: Summary of Recommended Pedagogy Style (RPS) corresponding to I^2A^2 learning style model

Learning Style (LS)	Key Terms	Recommended Pedagogy Style (RPS)
Imagistic (I)	Learn through seeing	Chart, diagram, symbols, picture, mind maps, videos, and flowcharts
Intuitive (I)	Learn through reading	Written notes, write idea in words, writing paragraphs, action charts
Acoustic (A)	Learn through listening	Group learning, listening, talking, reading notes, and underline information
Active (A)	Learn through doing	Hands-on exercise, color coding techniques, keywords, use models, extra exercise and experiments based work

4.4 DISCUSSION

The I^2A^2 LSQP has numerous applications in our perspective. First, the LSQP will give the direction to the pedagogues/educators on the assorted variety of learning styles inside their learning classes. This enables them to plan guideline that addresses the adapting needs of the greater part of the learner or understudies. Specifically, finding an extensive number of understudies with particular inclinations whose necessities are not being tended to should ready educators to the need to roll out a few improvements in their instructing.

Second, it gives to learner intuition into their conceivable learning qualities and shortcomings. Numerous learners who reliably experience issues with particular course and educators are slanted to put the accuse completely for poor instructing and acknowledge no moral obligation regarding their disappointments. Numerous other credits to the disappointments totally to their own particular insufficiencies and take full obligations.

In addition to that, I^2A^2 LSQP can be used in classroom education, business, e learning, and distance education program. Classroom education incorporates all parts of primary, secondary, higher education, engineering, and management education. This model can be used to identifying the learning styles of professionals in a company or an organization that leads in growing of their skills in learning. This can also be helpful for the corporate training to the trainees. In the present day, the e-learning education gained speed to minimize the time and effort and provides effective learning environments to the learner and educators. In the sense, a need of an adaptable tutoring system that incorporate such learning model. This model can be helpful to endow personalized environment and adaptive learning material.

I^2A^2 suggestions for education and teaching method, this recommends that the correct analysis of learners learning style, and the satisfactory coordinating of the learning condition and mentors' academic style with such learning preferences, are the way to encouraging training and enhancing learner performance and fulfillment. It contends that an assorted variety of instructional media such as textual, audio, and video is the favored way for teachers and students.

Thus, the I^2A^2 LSQP can be utilized to enable educators/teachers to accomplish adjusted course guideline and to enable understudies to comprehend their learning qualities and region for upgrades.

4.5 SUMMARY

This chapter discussed the innovative I^2A^2 learning style model along with its 4(four) LSD: Imagistic, Intuitive, Acoustics, and Active. The LSQP and the way toward recognizing the learning style of the student are examined. In this way, the prescribed instructional method relating to each learning style measurement of I^2A^2 learning style model has been investigated. At long last, the use of I^2A^2 learning style model is examined.

In the accompanying chapter, the design and architecture of the proposed tutoring system christened ‘SeisTutor’ along with its submodule will be discussed. The design of the course manager and the tutoring strategy will be presented.

CHAPTER 5: SEISTUTOR – A SEISMIC TUTOR

This chapter introduces the architecture of course manager, tutoring strategy, and the overall architectural design of the proposed adaptive ITS - SeisTutor. The architecture of SeisTutor covers the Learner Interface Model, Domain Model, Tutoring Strategy Model, and Learner Model along with their sub-models, which are the essential components of SeisTutor.

5.1 SYSTEM DESIGN

'SeisTutor' is an adaptive intelligent tutoring system for the subject domain of Seismic Data Interpretation (SDI). SeisTutor begins tutoring with the pre-tutoring tests (Domain Knowledge Tests and Learning Style Test). Pre-Tutoring tests help the framework to make the student's learning profile and dependent on the pre-tutoring tests score, suitable tutoring methodology is assigned to the learners. Based on the assigned learner profile, the system intelligently creates the best-suited learning contents and presents to the learner. The tutoring system incorporates the multimedia features in the learning process (Textual, Audio, or Video) into the learning process, which helps to improve learning.

SeisTutor offers three main functions: Observing, Tutoring, and Assessing. These functions do not exist independently however each contributes interestingly to the general execution of the framework. These functions are described as follows:

A. Observing

This functionality of the system, monitor the activities of the learner while learning and provides on-demand advice to the learner. The advice is based on learner situations and further action will be taken to provide appropriate course contents.

B. Assessing

Assessing functionality of the system, tracks the learner learning progress and records the results, report cards, explanations, hints, and feedbacks.

C. Tutoring

It creates and offers the appropriate tutoring strategies to the learner as per assigned learner profile. The tutoring system utilized numerous tutoring strategies to offer adaptive and personalized learning will be discussed in the later Sections.

Three types of users has been incorporated in the SeisTutor: The administrator, the learner, and the teacher. The administrator is a type of user, which takes control of the system and can create, modify, and change the system functionality. The learner is a type of user that communicates with the SeisTutor and that learn a particular lesson of seismic data interpretation. The teacher is a type of user who creates content and this is a domain or subject expert with special knowledge and skills in that domain, which is taught by the tutoring system. Each user (administrator, learner, or teacher) communicate to the tutoring system and authorized through the login process, which helps the system to manage the learning session of user.

5.2 CONTENT/COURSE MANAGER (CM)

The Content Manager provides entire learning material and the derivation component of the ITS. The primary objective of content manager is to enhance the learner performance through adjusting the learner data to provide best tutoring strategy. It also supports to keep the learner’s curiosity in improving the learning outcomes and motivations. The CM continually examines the learner’s actions through communication with AI modules, to adapt the tutoring strategy for each learner. It keep the records of all the learners’ activities and the respective outcomes of the system in a backend database file. The teacher approaches the backend file documents through the teacher interface to understand the degree of connection with the SeisTutor.

Each activity of the learner is sent to the content manager via the learner interface module, which decides how to react to it using the algorithm incorporated. When the submitted actions map to a specific issue, the CM transfer to the dashboard of learners that examines and updates the system. In view of the learner request, the CM may likewise produce a tutoring strategy that contains the lessons, quizzes, revisions, questions, or explanations. The main goal of the content manager is *'what to teach'* part of a system and to get a proper tutoring strategy which provides '*how to teach'* a particular learning content. The functionality of the content manager and tutoring strategy are shown in Figure 5.1.

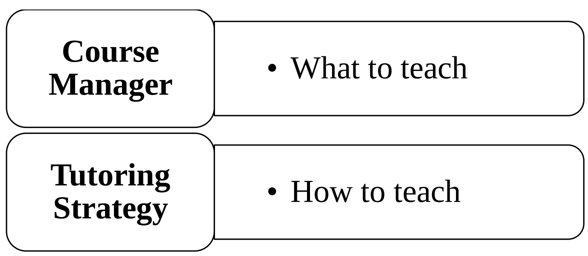


Figure 5.1 - Interaction of Course Manager and Tutoring Strategy

5.3 COURSE DESIGN

The aim of course design is to involve the learners through the active sessions in the learning. This uses the the acquirement of knowledge or skill through the direct understanding of completing a task. The course module is offered in various form such as lessons, quizzes, revisions, and examination sub-modules. In this module, the learner can learn to undertake focused tutoring strategy, which helps in developing the learner's knowledge. The whole course is divided into the four weeks and each week include n-number of lessons. For a Week (W), there are n Lesson (L), Quiz (Q), and Revision (R) corresponding to each Lesson (L). Each quiz has questions and every Question (Qn) has corresponding Hint (H). All the lessons, quizzes, revisions, and examinations may begin by representing the contents in textual form or may include the multimedia learning contents (audio, presentation, video, or images) to introduce the concept. The SeisTutor constitutes the course of Seismic Data Interpretation (SDI). The learning courseware with its different form is represented in Figure 5.2. The structure of the course map is presented in Figure 5.3.

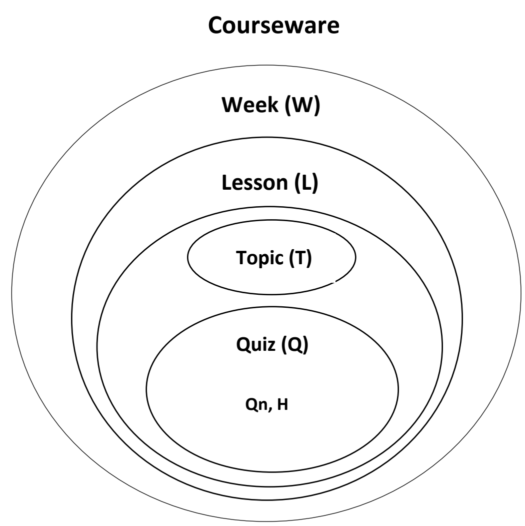


Figure 5.2 – Structure of SeisTutor Courseware

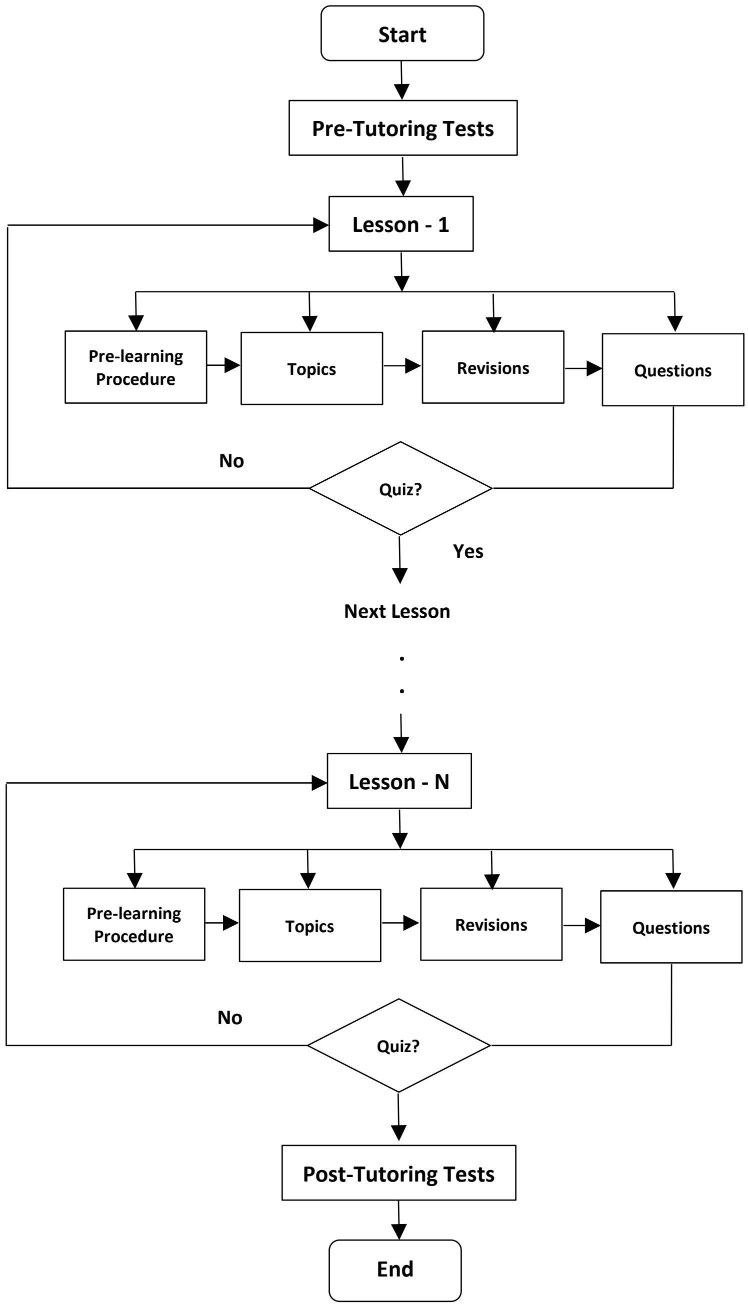


Figure 5.3 – Structure of the Course Map

5.3.1 Lesson (L) Module

The Lesson is a period of teaching of certain learning materials where understudies are taught about a specific exercise or how to play out a particular activity. Inside each exercise, the student finds learning materials, readings, practices for development, and associations with mixed media content, for instance, pictures, sound, or chronicles.

5.3.2 Quiz (Q) Module

The assessment or evaluation is an important part of any tutoring system. The quiz is the important ways to measure the knowledge of the learner. The Quiz (Q) has a set of questions and is presented week wise to the learner. Each Question (Qn) in the Quiz (Q) has a corresponding Hint (H), which supports to think the correct answer of the question. The learner must attempt the quiz before proceeding to the next week lessons.

5.3.3 Revision (R) Module

Revision of a lesson is a technique to improve the learning through the repetitive practices. This is used to get the information through practicing lesson content provided by the Lesson model. Revision offers sample questions along with responses that helps learners to assess themselves before attempting the required quiz or assignments. (Anderson and Elloumi, 2004).

5.3.4 Examination (E) Module

In the assessment module, there is a lot of inquiries expected to choose the student's information at a specific learning level (Beginner, Intermediate, or Expert). There a pre-tutoring test toward the start of the course to initiate the tutoring, which is intended to test his/her initial knowledge to put them in a particular class or learner profile. In the examination module, we conduct a post-tutoring test when completion of all learning contents. The learner must submit final examination (post-tutoring test) to know the progress of learning.

5.4 TUTORING STRATEGY (TS) DESIGN

The tutoring of the learning material is depended on the different tutoring strategy. The teacher can create and modify the tutoring strategy with the help of teacher model. The design of tutoring strategy helps the tutoring system to select appropriate tutoring strategy to the learner based on the tutoring parameters. Table 5.1 presents the tutoring parameters and Table 5.2 presents the structure of the tutoring strategy contained in 'SeisTutor'.

Table 5.1 - Tutoring Strategy Parameter

TS Parameters	**Values**			
Learner Level (LL)	Beginner	Intermediate		Expert
Learning Style (LS)	Imagistic	Intuitive	Acoustic	Active

Table 5.2 - Structure of Tutoring Strategies in 'SeisTutor'

S.N.	**Tutoring Strategies**	**Learner Level (LL)**	**Learning Style (LS)**			
			Imagistic	**Intuitive**	**Acoustic**	**Active**
1	TS1	Beginner	✓			
2	TS2	Beginner		✓		
3	TS3	Beginner			✓	
4	TS4	Beginner				✓
5	TS5	Intermediate	✓			
6	TS6	Intermediate		✓		
7	TS7	Intermediate			✓	
8	TS8	Intermediate				✓
9	TS9	Expert	✓			
10	TS10	Expert		✓		
11	TS11	Expert			✓	
12	TS12	Expert				✓

Based on the tutoring strategy design, the combination of the dimensions of tutoring parameters is developed and then it is mapped with a specific tutoring strategy. There are twelve combinations of various tutoring strategies are created. Each combinations is represented a distinctive strategy and every strategy is pre-characterized based on the inputs tutoring parameters. Each group is mapped with the lessons to provide the appropriate tutoring strategies to learner.

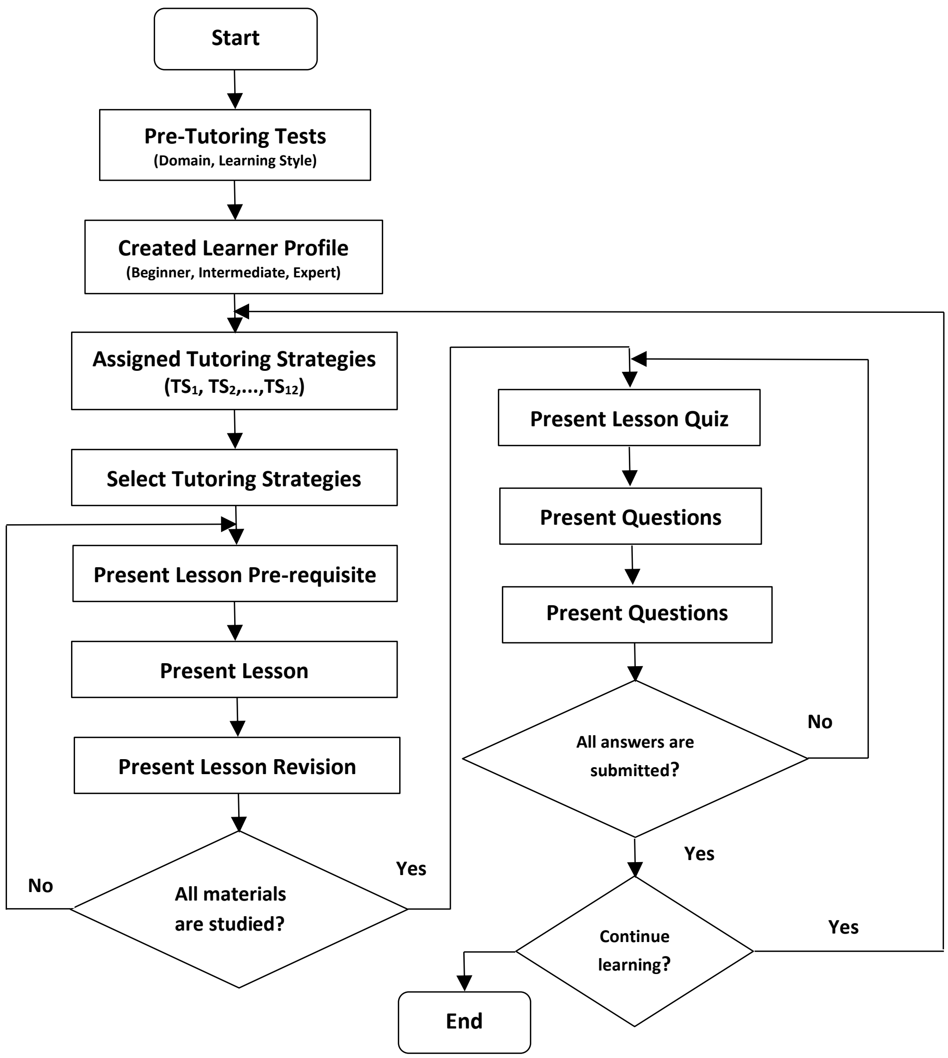


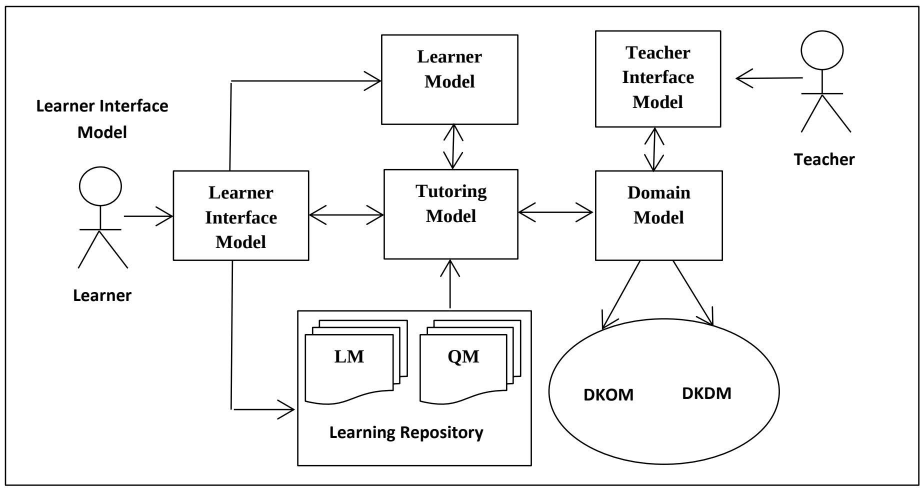
Figure 5.4 – Design of Selection of Tutoring Strategy (TS)

Based on the tutoring strategies (TS_1, TS_2…, TS_{12}), each combinations of the tutoring strategy parameters (see Table 5.1) is mapped to a certain tutoring strategy. There are twelve groups of tutoring strategy has been developed and each tutoring strategy is according to the input parameters and having different media contents (text, audio, video, and images). The design of the selection of tutoring strategy to the different groups of learner are presented in the Figure 5.4 above.

5.5 ARCHITECTURE OF 'SEISTUTOR'

The proposed adaptive intelligent tutoring system is christened 'SeisTutor'. It is a computerized educational framework written in C# on .net framework, which gives an adaptive educational framework to the learner by offering easy and customized learning material for the subject domain of Seismic Data Interpretation (SDI). It offers the learner with an assortment of materials according to the preference and learning styles of learner, with various media and various teaching methods of explanations (Wenger, 1986; Chou et al, 2003). We have divided the architecture of an ITS with four essential modules that is presented in Figure 5.4.

Domain Model is sometimes referred to as an expert or content model contains the learning content/material that will be instructed to the student and is considered as a wellspring of information. This model has two primary parts. The first is known as Domain Knowledge Object Model (DKOM), which contains the specific information base of the area. The second is the Learning Repository, which contains the metadata clarified exercise and test materials. ***Learner Model*** stores data about the student's earlier information, student execution, learning style, psychological capacities, learning styles, and inclinations. This module gives the reason for the adaptation rules used by the ITS. ***Tutoring Model*** settles on the choice about tutoring techniques dependent on the data gave by the student and the domain models and afterward executes the specific instructing process. Legitimately, this module lies in the point of convergence of the framework and by associating with every single other module. It gives adaptive rules to the students. ***Learner Interface Model*** permits the framework to collaborate with learners. All learning materials and test sets are acquainted with the learner through this interface and test results are utilized for evaluation of learner performance. The engineering model of 'SeisTutor' is presented in Figure 5.5. We talk about its various modules and their functionalities in detail in the next Section.



DKOM: Domain Knowledge Object Model, DKDM: Domain Knowledge Database Model,
LM: Lesson Model, QM: Quiz Model

Figure 5.5- Architecture of Proposed Intelligent Tutoring System - SeisTutor

5.6 COMPONENT MODULES OF SEISTUTOR

5.6.1 Learner Interface Model (LIM)

LIM is the gateway of the adaptive tutoring framework for interacting with the learner. This interface is used to display all the learning materials, assignments, quiz sets and performance result of the learner.

5.6.2 Domain Model (DM)

The Domain model is represented as knowledge model and considered as a source of knowledge driven by the tutoring framework. This model contains the subject information base of the 'SeisTutor'. It sorts out the course structure, its various segments, and the relationship among them. This model fundamentally deals with the what-to-show segment of SeisTutor (Wenger, 1986; Murray et. al., 2003).

5.6.2.1 Domain Knowledge Organization Module (DKOM)

DKOM presents the structure and association of the course and its exercises and association between the course topics. It is otherwise called the information base of the mentoring framework and this module characterizes the basic portrayals of various subjects. The data structure used to speak to the course will be *Course Tree Structure (CTS) and Course Dependency Graph (CDG).*

Course Tree Structure (CTS)

CTS is a hierarchical portrayal of a course, which is put away in the mentoring framework. The root node for example parent node of the tree represents the name of the course (SDI). Subsequently, the different child node/sub-child node and the topics have put in a leaf node (lower part) of the tree representation. The complete course is divided into four weeks. Every week contains the lessons and each lesson contains various topics. Figure 5.6 presents the tree structure of the course (SDI).

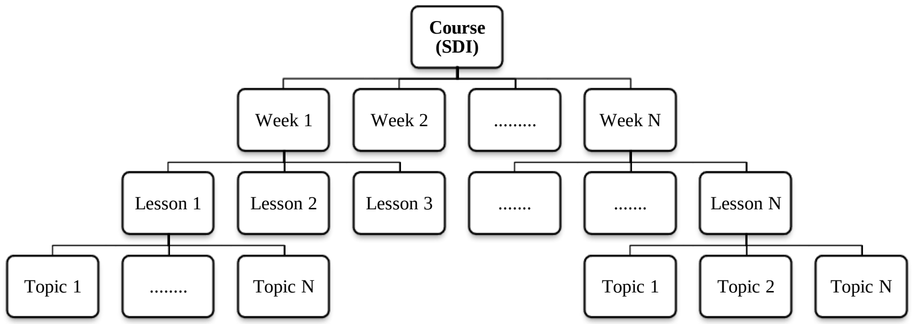


Figure 5.6 – Course Tree Structure (CTS) - SDI

Course Dependency Graph (CDG)

The nodes in CDG are comprised of the subjects from the CTS. The edges between the points represent the essential connection between the different topics. Figure 5.7 presents the course dependency graph.

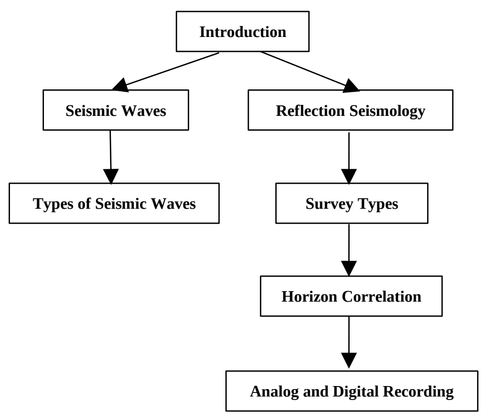


Figure 5.7 – Course Dependency Graph (CDG) - SDI

5.6.2.2 Domain Knowledge Database Module (DKDM)

DKDM is a pool for the learning material. All of the learning material, quizzes, hints, feedback are stored in this pool. For effective access to materials from the pool, the materials are labeled with different naming conventions. These naming conventions provide a depiction of the document, which helps in the retrieval of the appropriate learning content in a proficient and customized manner. In addition to that, for tagging learning material, a naming convention has been used.

5.6.3 Learner Model (LM)

The most critical undertaking of an intelligent tutoring system is the utilization of its "intelligence". This implies applying distinctive tutoring strategies for instructing to various learners, with no intercession from the classrooms human instructor. To choose the technique for instructing, the framework must think about the nature, needs, strength and inclinations of the learners. Tutoring can be best when the learners need, knowledge level, subjective capacity, his or her behavioral can be legitimately evaluated from his or her learning result. Calling attention to learners lacks and focusing on those areas is a crucial stage in any tutoring procedure and can unquestionably bring about a pickup in his or her learning performance. In this learning condition, there is no other human contribution separated from the learners. Henceforth, an instrument or a utility is required inside the framework, which will intervene between the framework and the learner. This device ought to have the capacity to evaluate the learner legitimately and give the intelligent decision making power of the framework with all the relevant material, for example, learner limitation, which is required for adapting tutoring, which is known as the learner model.

A vigorous adaptable and far-reaching learner model is very crucial for an Intelligent Tutoring System. In a perfect, a learner model should keep the intellectual ability, need, preferences, and objectives of the learner as it is a dynamic portrayal of the learner. Like typical educating, where the human teacher responds and dynamically changes the pedagogy as indicated by the criticism gotten from the learner, the pedagogical model in ITS must adjust and alter the tutoring strategies as indicated by the input gotten from the learner model. We likely planning such a learner model which have the capacity to furnish the framework with all the necessary learner details and mentioned characteristics. These details should be adequately utilized by the pedagogical model to give the learner customized learning material, addressing the requirements of the individual leaner. In this way, an all-around outlined learner model is fundamental in meeting the targets of ITS.

5.6.4 Tutoring Model (TM)

It is the educational specialist of the framework and it executes the genuine instructing process. From an intelligent perspective, this module lies in the focal point of the framework and by comminicated with different modules, it gives versatile learning materials to the understudies.

5.7 SUMMARY

The design and architecture of developed tutoring system christened 'SeisTutor' with its sub components is discussed. The design of the Course Manager (CM) and Tutoring Strategy (TS) is discussed. Subsequently, the components of the CM such as Lesson Module, Quiz Module, Revision Module, and Examination Module is explored. Additionally, the component of tutoring strategy and the design of selection of tutoring strategy is presented. The TS architecture design presents the personalized tutoring strategies for educating a specific lesson/topic to the learners.

In the following chapter, the implementation of SeisTutor and along with its component's will be discussed. The Data Flow Diagram (DFG) of the SeisTutor and its sub components will also be discussed.

CHAPTER 6: IMPLEMENTATION OF PROTOTYPE ITS-SEISTUTOR

The design and implementation of SeisTutor along with its modules and submodules, which incorporates learner model, tutoring model, adaptation model, domain model, and learner interface model is presented in this chapter. The learner model includes components and its subcomponents- the learner characteristics model, the learner classification model, and the learner adaptation model. The DFD of all the components and subcomponents of SeisTutor is presented to display the flow of data.

6.1 IMPLEMENTATION OF THE SYSTEM

SeisTutor is coded using C# .net framework and C# fuzzy library. Data storage is through MS Access database running on Windows platform. This is a standalone offline application compatible to Window platform.

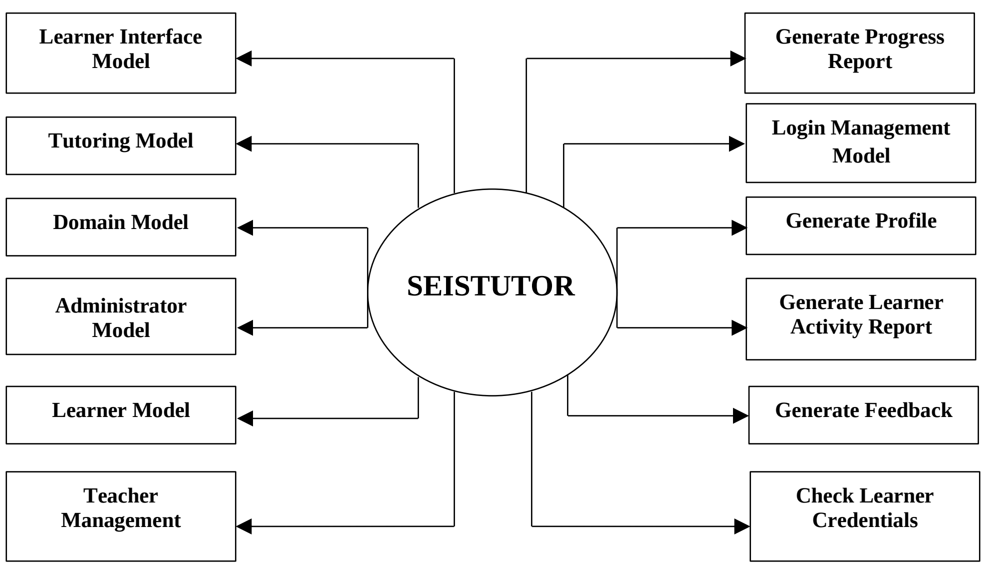


Figure 6.1: Level 0 - DFD of SeisTutor

6.2 LEARNER INTERFACE MODEL

The Learner Interface Model (LIM) is a crucial component that provides the communication between system and learners. The LIM helps the learner for studying, and teacher to design the appropriate teaching material over learning process. The learner interface model also helps the learner to display their results and transcriptions. The LIM facilitates personalized interaction mode of learning, which help the learner to get personalized learning materials.

The User Interface (UI) or Graphical User Interface (GUI) assumes a significant role to introduce the system functionalities and provides cooperation between the learners and the tutoring system framework. UI is intended to be easy to use for the teachers and the learners alike. The developed prototype - SeisTutor has two UI's: first, learner interaction and teacher interaction (discussed in Section 3.6). Figure 6.1 presents the main window of the learner interface model.

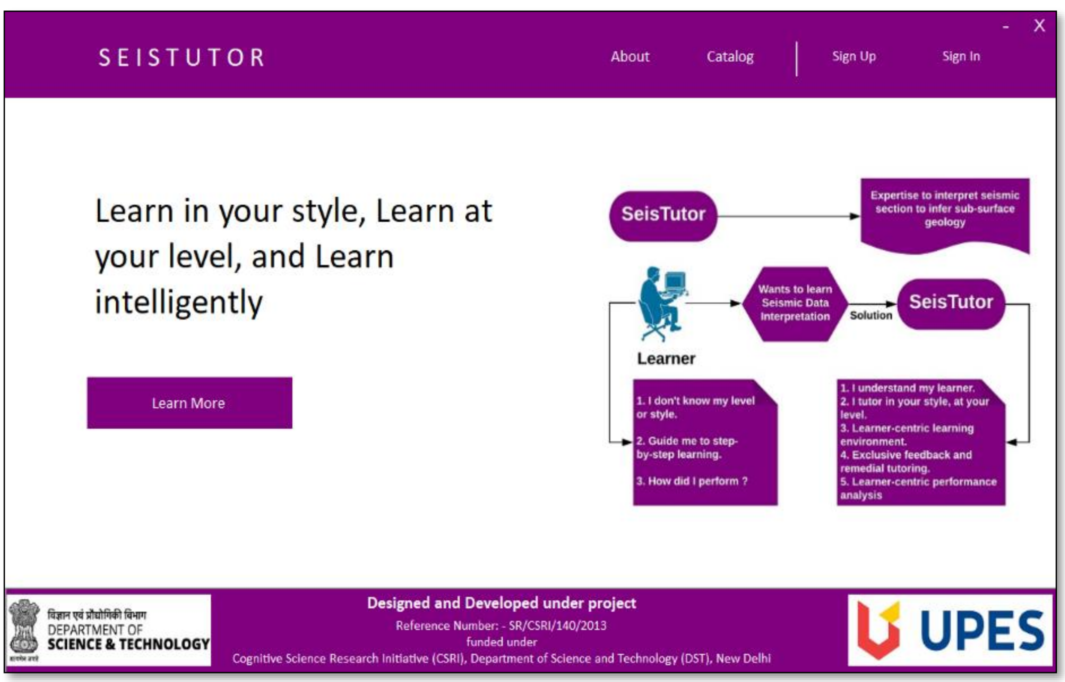


Figure 6.2: Main Window of the Learner Interface

The GUI is additionally used to demonstrate the learning material through different media forms like pictures/images, audio, and video. Besides the GUI has utilized as a software program for demonstration of contents in a mixture of these media forms. The LIM offers the lesson explanation, hint, feedback, and the learning statistics to the learner. The LIM has the learner registration interface that allows the learner to log in to the SeisTutor.

6.2.1 Learner Registration

The learner registration control allows the learner to register with the tutoring system. The learner enters the username, email id, and password to create unique learner id. The unique learner id is used to manage the tutoring sessions and record the learner statistics which helps the system in decision making. Figures 6.3 and 6.4 present learner registration process flow and learner registration interface respectively.

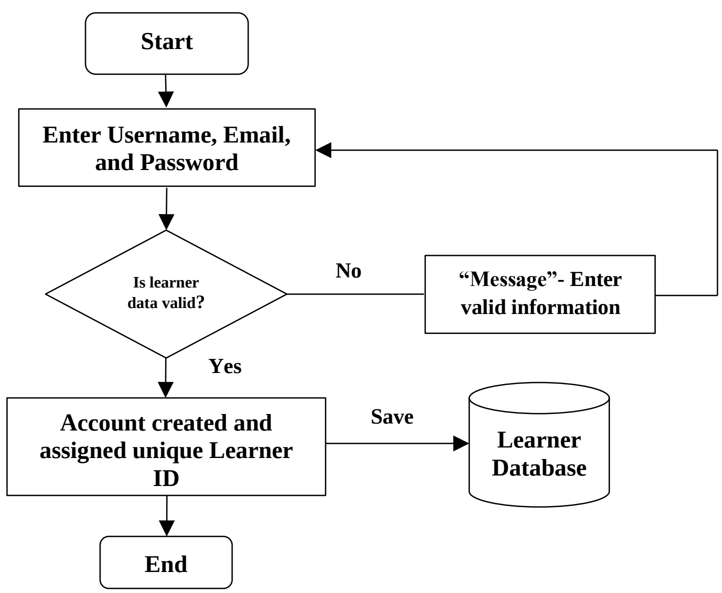


Figure 6.3: The Process of Registering to SeisTutor

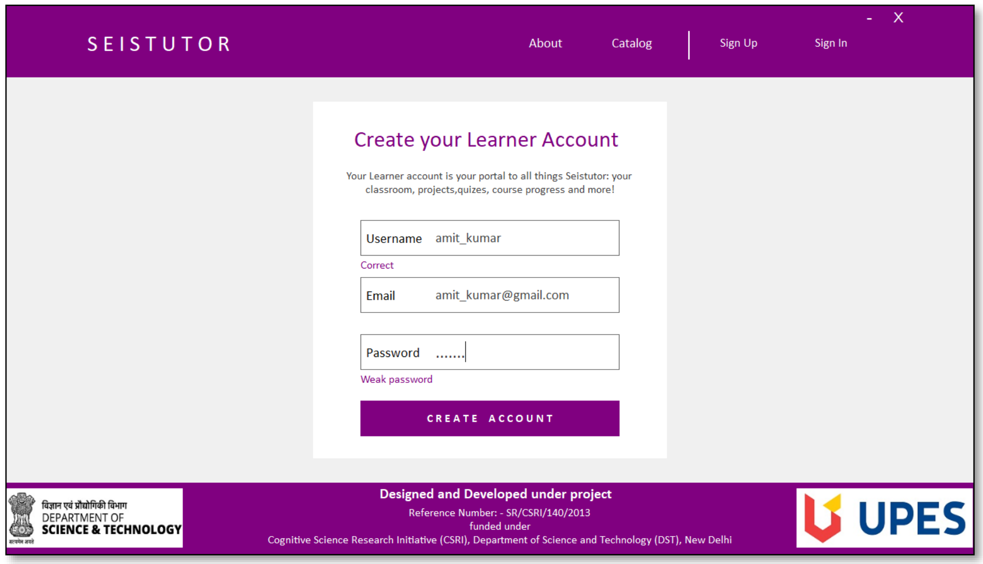


Figure - 6.4: Learner Registration Interface

6.3 DOMAIN MODEL

The domain model sometimes referred to as an expert model and known as knowledge base of framework i.e. 'SeisTutor'. It organizes the structure of the course presented, its components, and interconnection between components. The domain model represents *'What-to-teach'* component of the SeisTutor. Figure 6.5 presents the DFD for the domain model

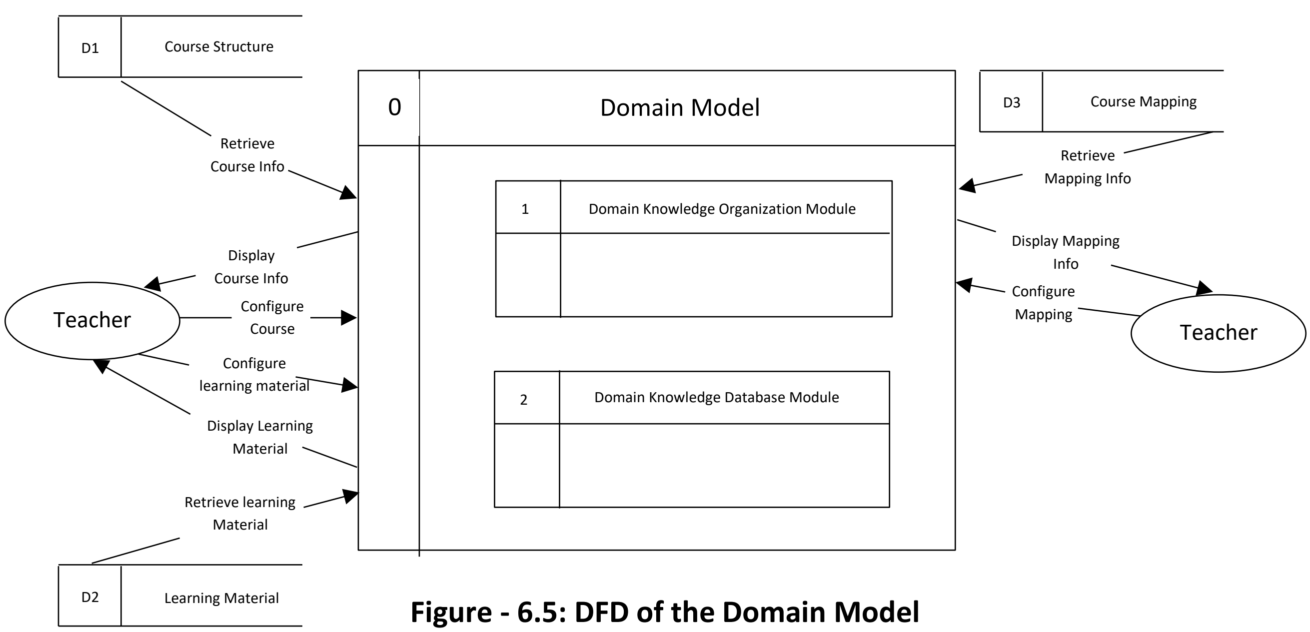


Figure - 6.5: DFD of the Domain Model

The domain model consists of two subcomponents. First, the Domain Knowledge Organization Module (DKOM), which contains the structure of the domain and organizes the course in ease to understand manner. Second, the Domain Knowledge Database Module (DKDM) that stores the learning and test material in the database. The learning content is represented with the metadata attributes or course annotations. The annotations forms of learning content help the system to reuse and track the learning content from the knowledge base of the SeisTutor. The course mapping is done by the teacher through the teacher interface module. Figure 6.6 presents the domain model interface.

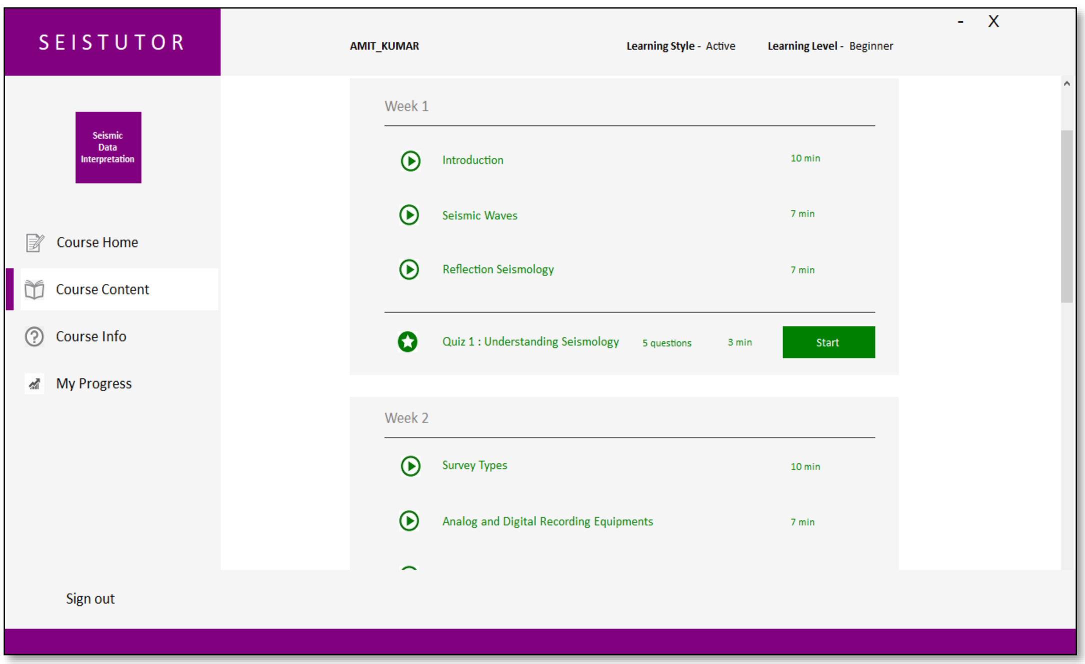


Figure - 6.6: Domain Model Interface

6.4 LEARNER MODEL

The learner model is one of the critical segments of SeisTutor. It holds the student data, for example, his/her competency level, learning style, intellectual and meta-psychological abilities. The fundamental errand of SeisTutor is to execute knowledge to create a proper mentoring procedure and suggest most appropriate learning content. The area information and learning style of the student is the most significant attribute of students and might be used to improve the exhibition of the coaching framework from multiple points of view.

First, domain knowledge can be utilized to judge the competency level (Beginner, Intermediate, and Expert) of learner that can be benefited to offer the learning material based on his/her competency. The snapshot of Domain Knowledge Test (DKT) interface is shown in Figure 6.7. In addition, learning contents matching with their learning style makes learning easier, effective and adaptive (Tseng, Chu, Hwang, & Tsai, 2008). Figure 6.8 and Figure 6.9 presents the Learning Style Test (LST) and Domain Knowledge Test interface.

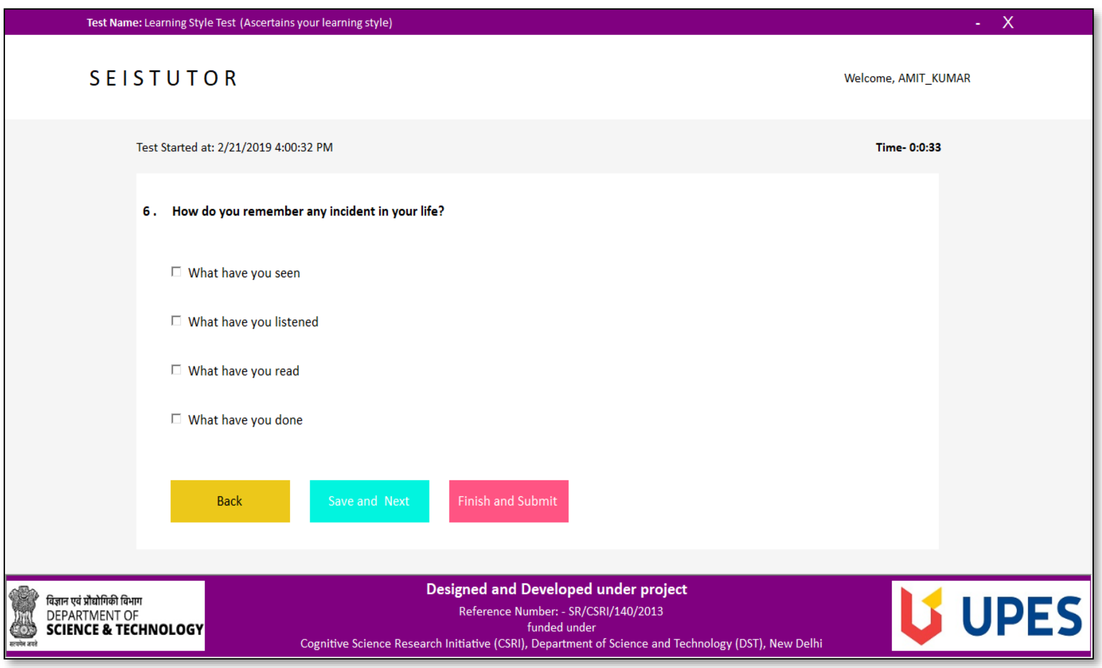


Figure 6.7: Learning Style Test Model Interface

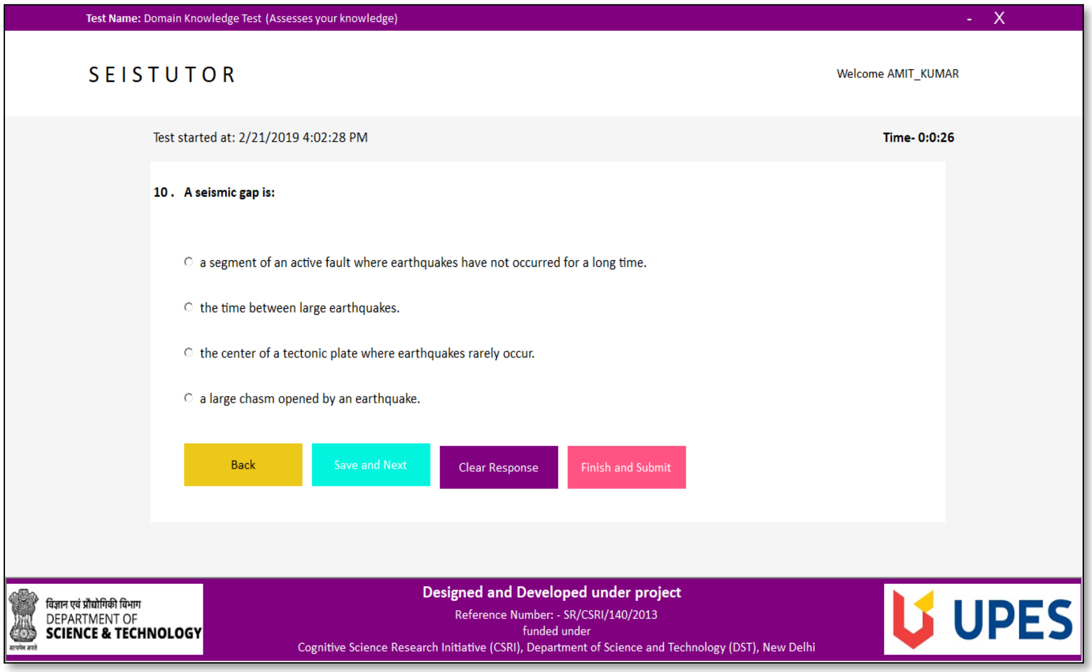


Figure 6.8: Domain Knowledge Test Model Interface

Learner model is classified under three sub-models, learner characteristics model, learner classification model, and learner adaptation model. Figure 6.9 presents the DFD for the learner model and its submodels.

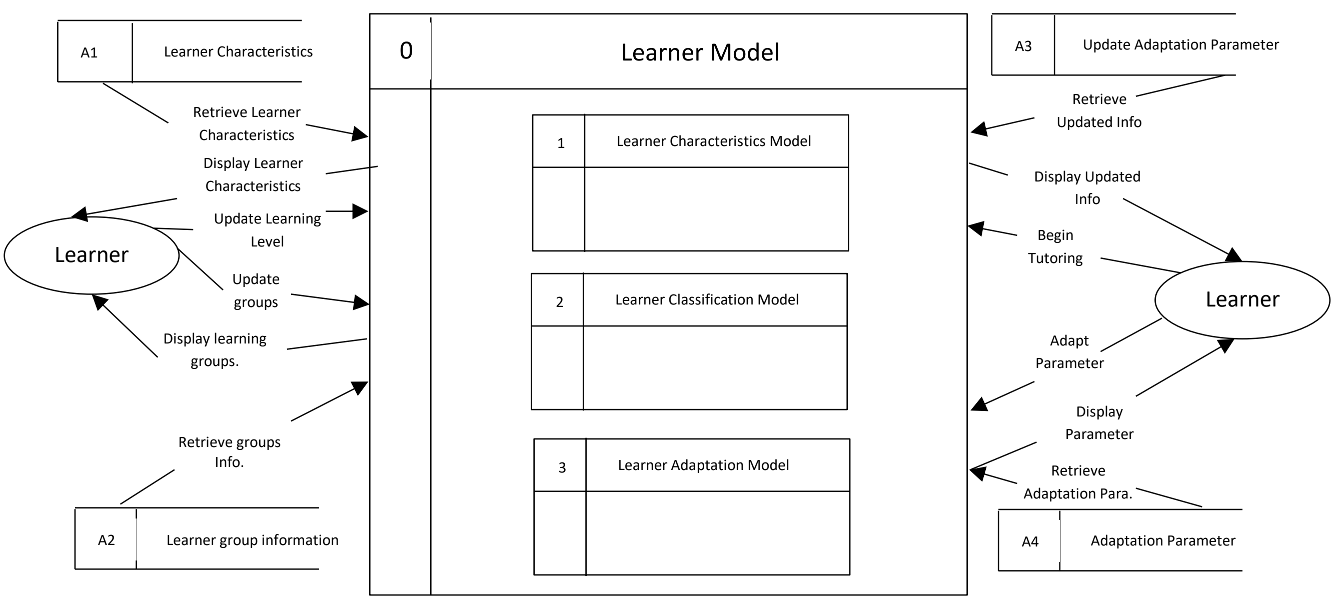


Figure 6.9: DFD of the Learner Model

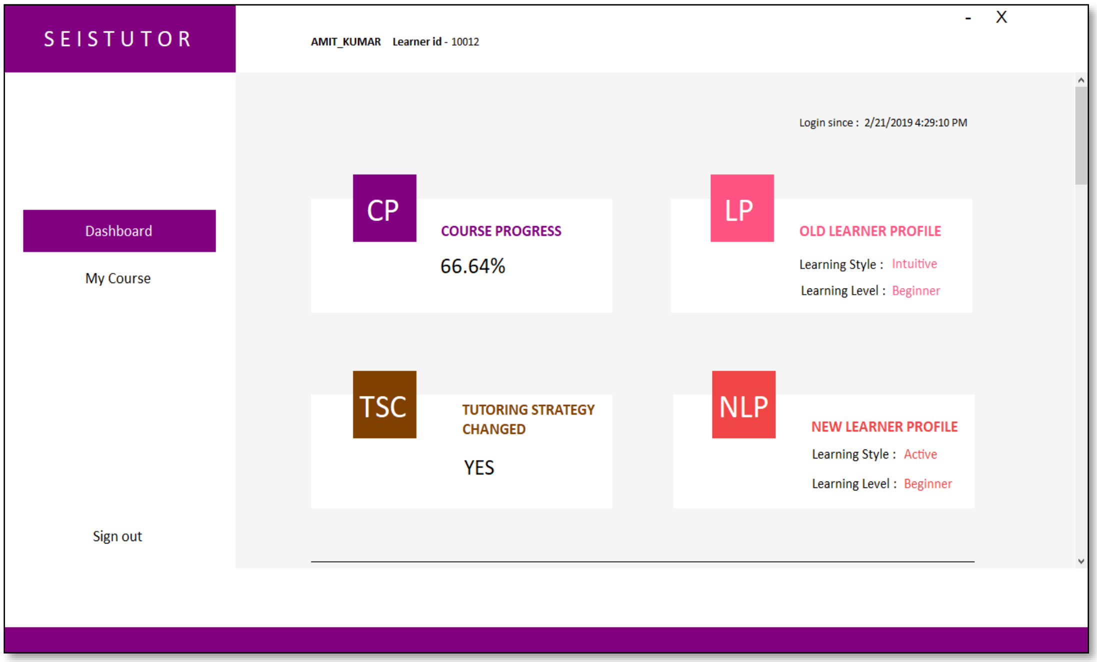


Figure - 6.10: The Learner Model Interface

The learner characteristics model holds student qualities, for example, subject information, learning style, intellectual and meta-psychological aptitudes. The student characteristics help the framework to decide the stereotype (Beginner, Intermediate, or Expert) of a student. The learner classification model categorizes the learner into groups based on the data received from the previous model. The learner adaptation model provides the adaptive tutoring strategy to learners (for details refer to Chapter 5). The screenshot of the learner model interface is presented in Figure 6.10.

6.5 TUTORING MODEL

The tutoring model is an essential component of SeisTutor that controls the tutoring processes. It is the heart of SeisTutor that communicates with other system models and provides the best suited tutoring strategy to the learner. Tutoring model communicates with the learner model and sequence the learning contents for a particular domain (Brusilovsky & Millan, 2007; Brusilovsky, P., & Vassileva, J., 2003). In SeisTutor, the tutoring model is divided under five sub models: administrator model, tutoring strategy model, pre-learning procedure model, lesson model, and quiz and hint model. Figure 6.11 and Figure 6.12 presents the DFD of the tutoring model and tutoring model interface.

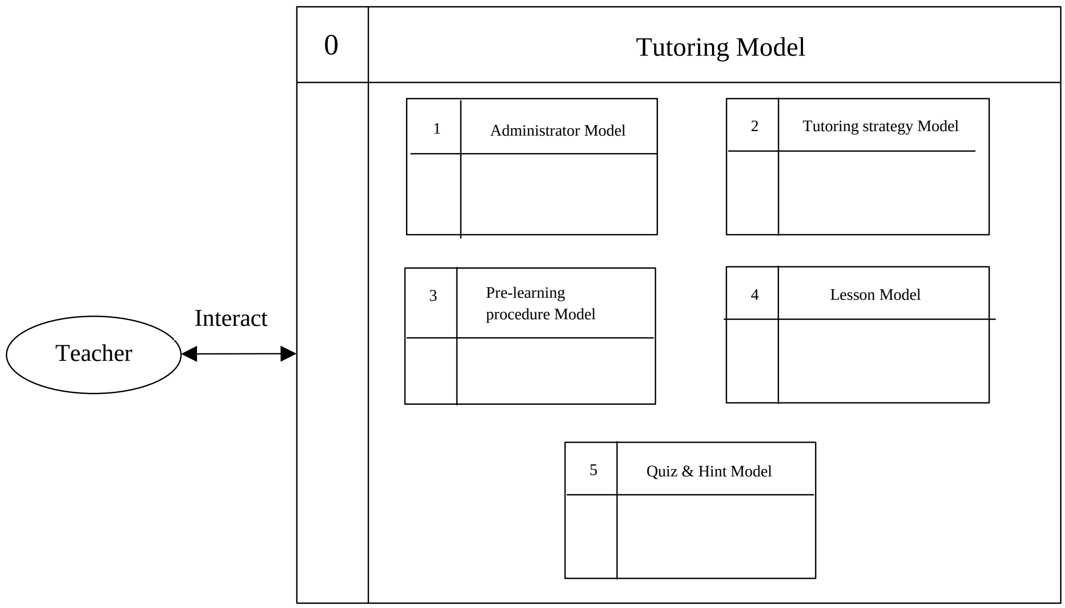


Figure - 6.11: A DFD of the Tutoring

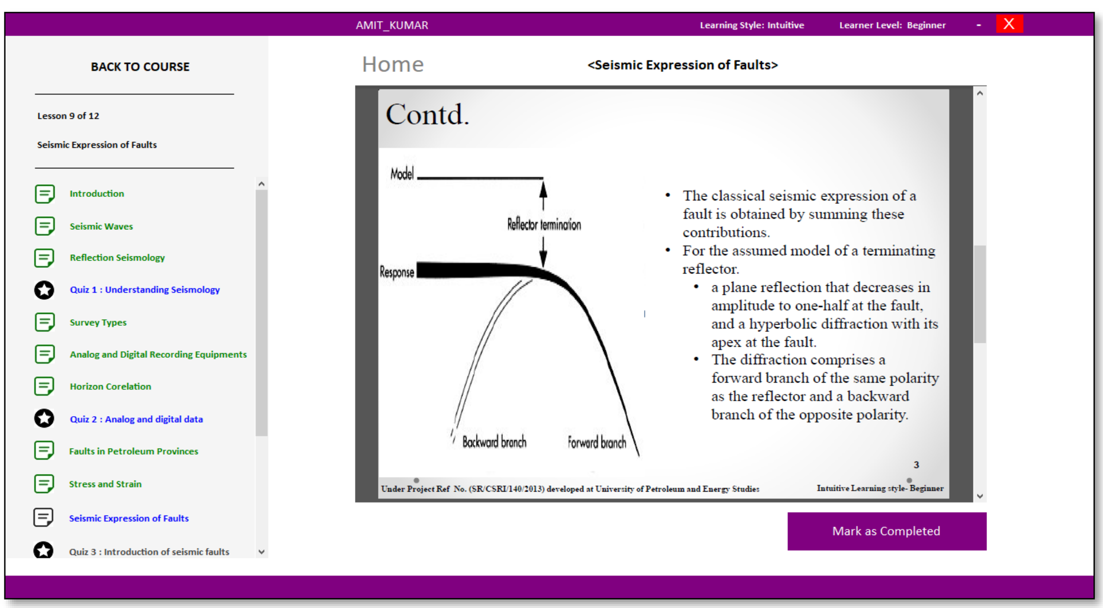


Figure - 6.12: The Tutoring Model Interface

6.5.1 Administrator Model

The administrator model allows for access to additional privileged, that learner or teacher cannot access. The administrator model can notice the learner's preliminary information such as registration, background information, and learning progress/statistics. Figure 6.13 presents the DFD for the administrator model.

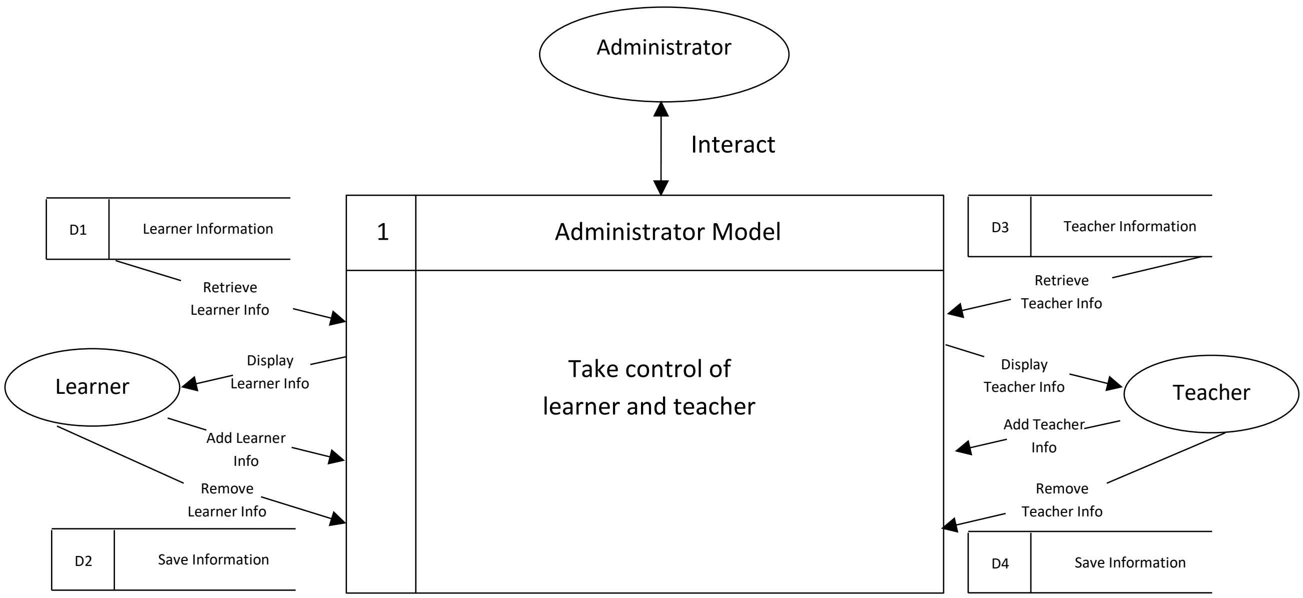


Figure - 6.13: A DFD for Administrator Model

6.5.2 Tutoring Strategy (TS) Model

Based on the competency level and learning style of learner, tutoring model generates the best-suited pedagogy for the learner. Tutoring strategy is the pedagogy offered to the learner. The SeisTutor formulates 12 (twelve) types of tutoring strategy for the learner based on his/her competency level and learning style (refer section 5.5). The tutoring strategy model is composed of two sub-models: Tutoring Strategy Selection Model and Tutoring Strategy Adaptation Model. The tutoring strategy selection model formulates the personalized tutoring strategy for the learners and sequences the learning material accordingly. The tutoring strategy adaptation model tracks the learner course progress for the offered pedagogy. The adaptation model also computes quantitative parameters such as scores, the time-taken, and hints taken during an ongoing quiz. The fuzzy inference rules have been coded and used on the parameter and fuzzy value is used to quantify adaptation and personalization of the learning material. Figure 6.14 and Figure 6.15 presents the DFD of the tutoring strategy model and the change tutoring strategy interface.

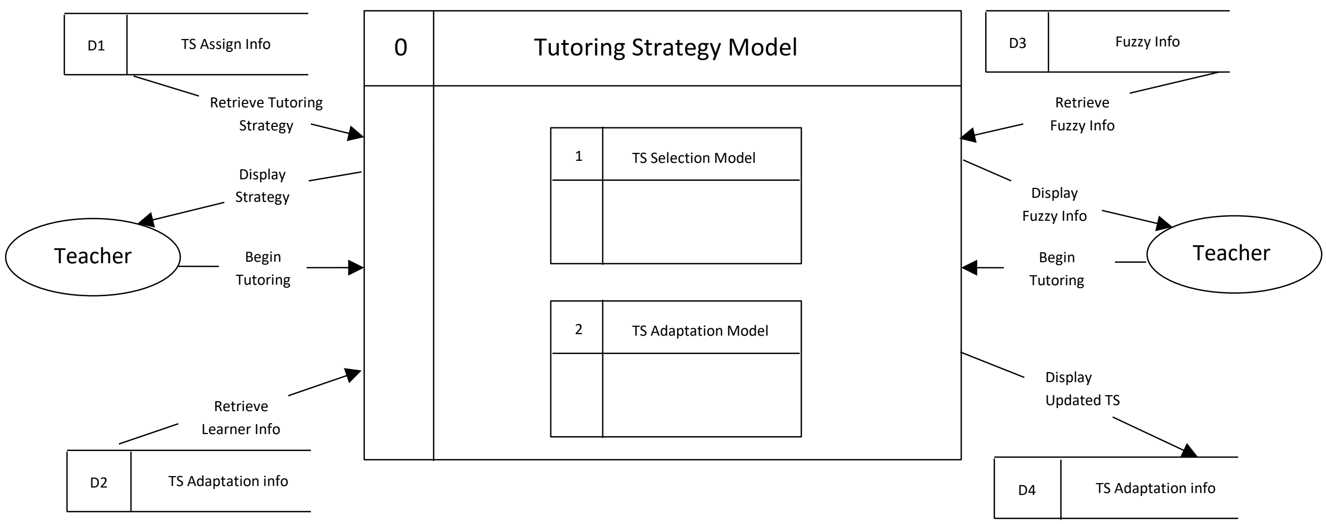


Figure - 6.14: DFD for Tutoring Strategy Model

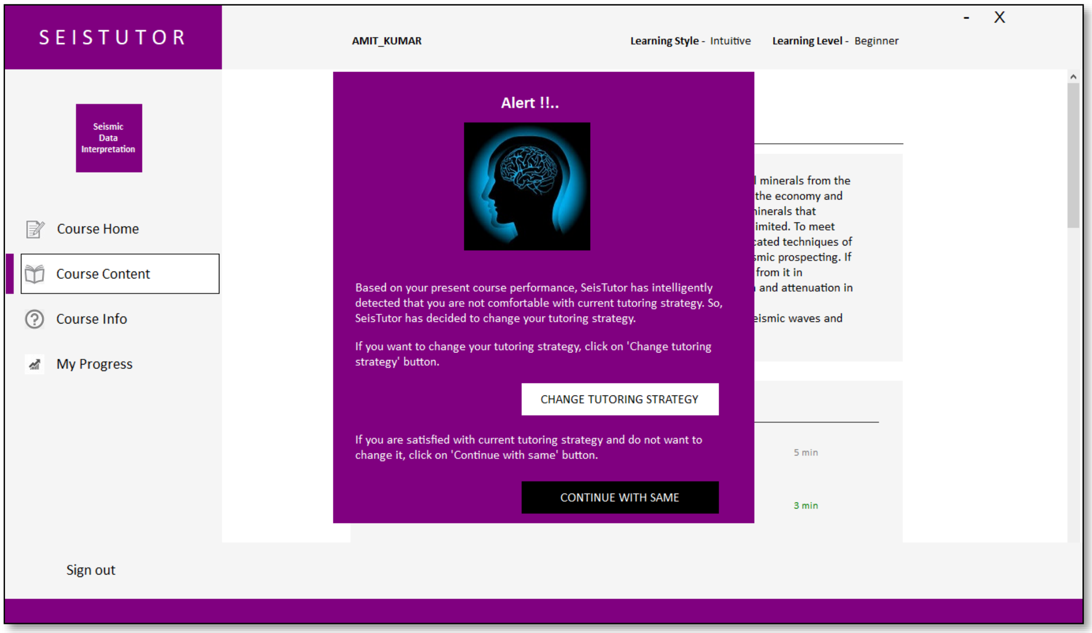


Figure - 6.15: The *'Change Tutoring Strategy'* Interface

6.5.3 Pre-learning Procedure Model

The pre-learning procedure model comprises the prerequisite guidelines that represent how to proceed to learn or intract with the SeisTutor. The pre-learning procedure is defined for each component and sub-components of SeisTutor such as pre and post-tutoring model, lesson model, explanation model, and revision model. The DFD for pre-learning procedure model is shown in Figure 6.11.

6.5.4 Lesson Model

This model presents the lesson contents to the learner for the domain of SDI. The DFD for lesson model and its submodules is shown in Figure 6.16. The lesson model allows navigating to the other lesson components: revision model, explanation model, pre-learning procedure model, and question model. The revision model facilitates the learner to revise the learning contents. Learners can revise contents any time with repetitions and generated statistics are recorded to the database file. The explanation model exhibits the learning material the learner by the explanation model interface. The question model provides questions to assess the understanding of the learned concepts. The file structure of the question is stored in 'QuestionsTextFile' and shown in Table 6.1. The learner progress pointers have been also provided to the lesson interface that displays the learning level, learning style, and current learning progress of the learner.

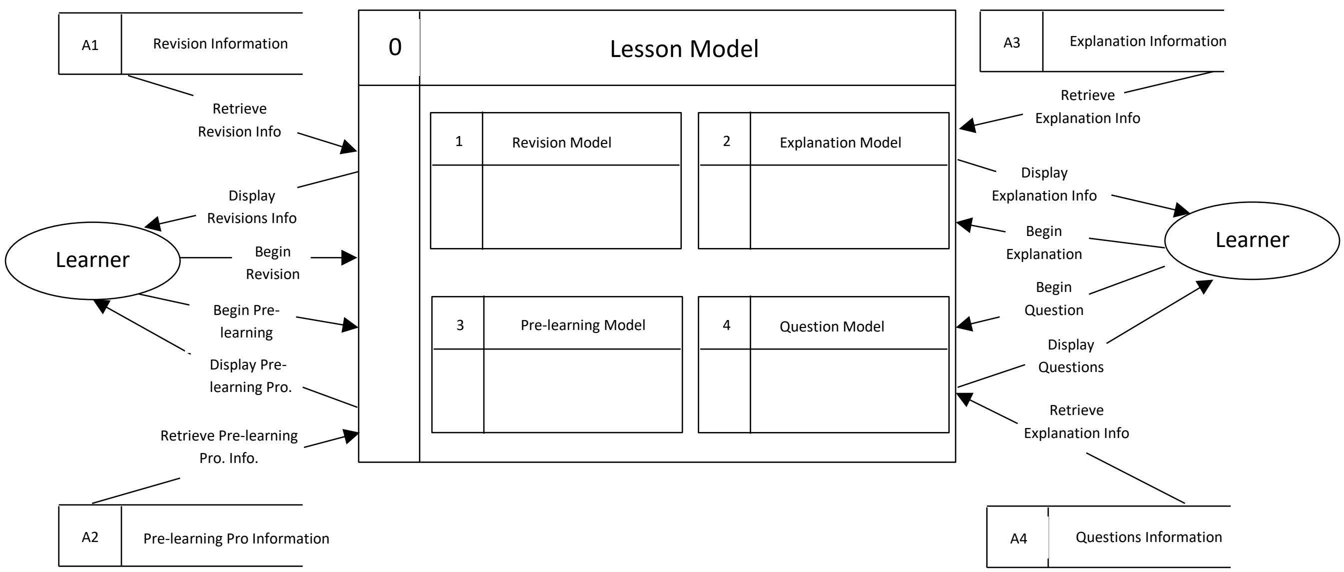


Figure 6.16: DFD for Lesson Model

Table 6.1: The Structure of 'QuestionTextFile'

S.N	Fields	Descriptions
1	QuestionID	The unique id of question
2	QuestionName	The name of the question
3	QuestionLevel	Competency level of question i.e. beginner, intermediate, or expert level
4	QuestionOptions	Options corresponding to questions
5	Answer	The answer to a certain question
6	QuestionHint	Hint corresponding to each question

6.5.5 Quiz and Hint Model

The overall tutoring sessions have been divided into lessons and each lesson has a quiz to assess the basic understanding of knowledge of the learner. The quiz is used to assess the learner knowledge based on selected tutoring strategy by the learner. Each quiz has questions and every question (q_n) has corresponding hints (h_n): (q_n -> h_n). The hints have been provided on the request of the learner corresponding to each question. Figure 6.17 presents the quiz model interafce. The quiz and hint process has been presented in Figure 6.18. The structure of the quiz is stored in the file *'QuizTextFile'* shown in Table 6.2.

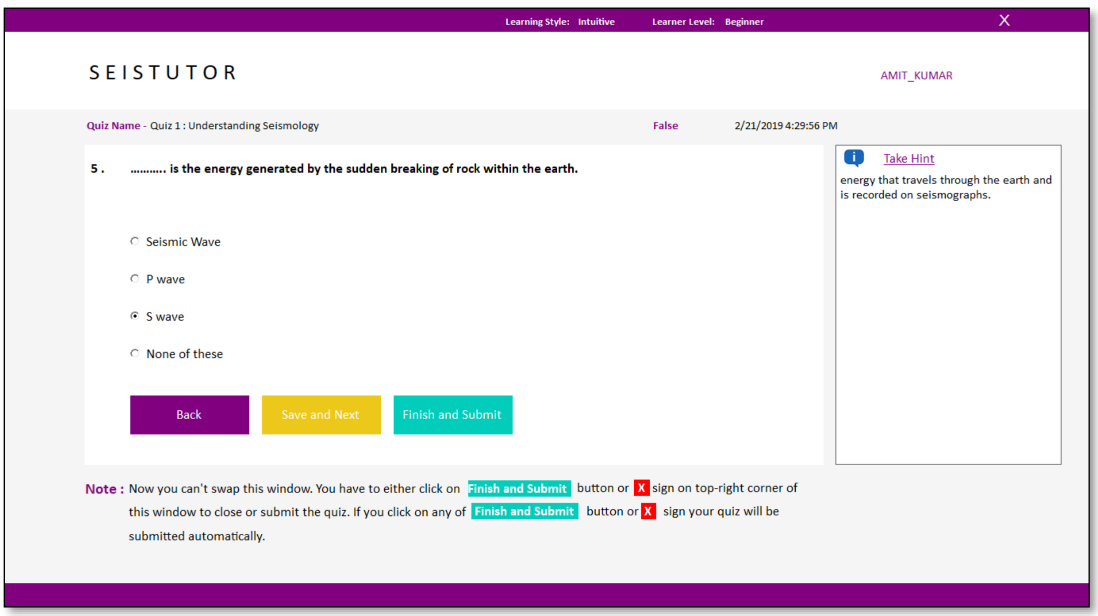


Figure - 6.17: The Quiz and Hint Model Interface

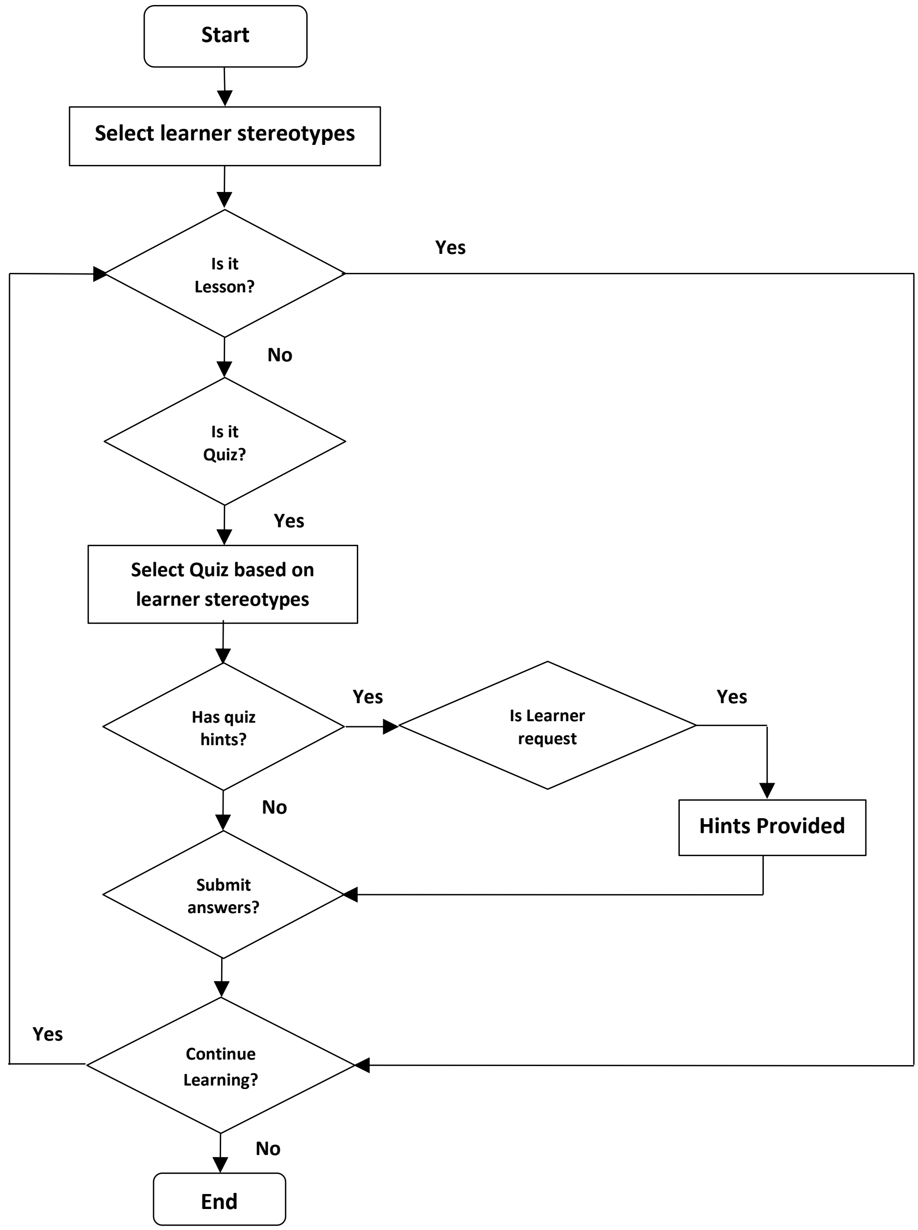


Figure 6.18: The Process of Quiz and Hint

Table 6.2: The structure of 'QuizTextFile'

S.N	**Fields**	**Descriptions**
1	Quiz ID	The unique id of the quiz
2	Quiz Type	Type of quiz subjective or objective
3	Quiz Level	Competency level of quiz i.e. beginner, intermediate, or expert level
4	Quiz Hints	Quiz hints have been provided or not

6.6 TEACHER INTERFACE

This interface provides the communication bridge between teacher and SeisTutor. It contains various components that helps the teacher to customize and update the personal information, learning material, quizzes, structure of course, and quiz time, course session time and can see the log file that contains all the learning session data. Figure 6.19 presents the organization of the teacher interface model.

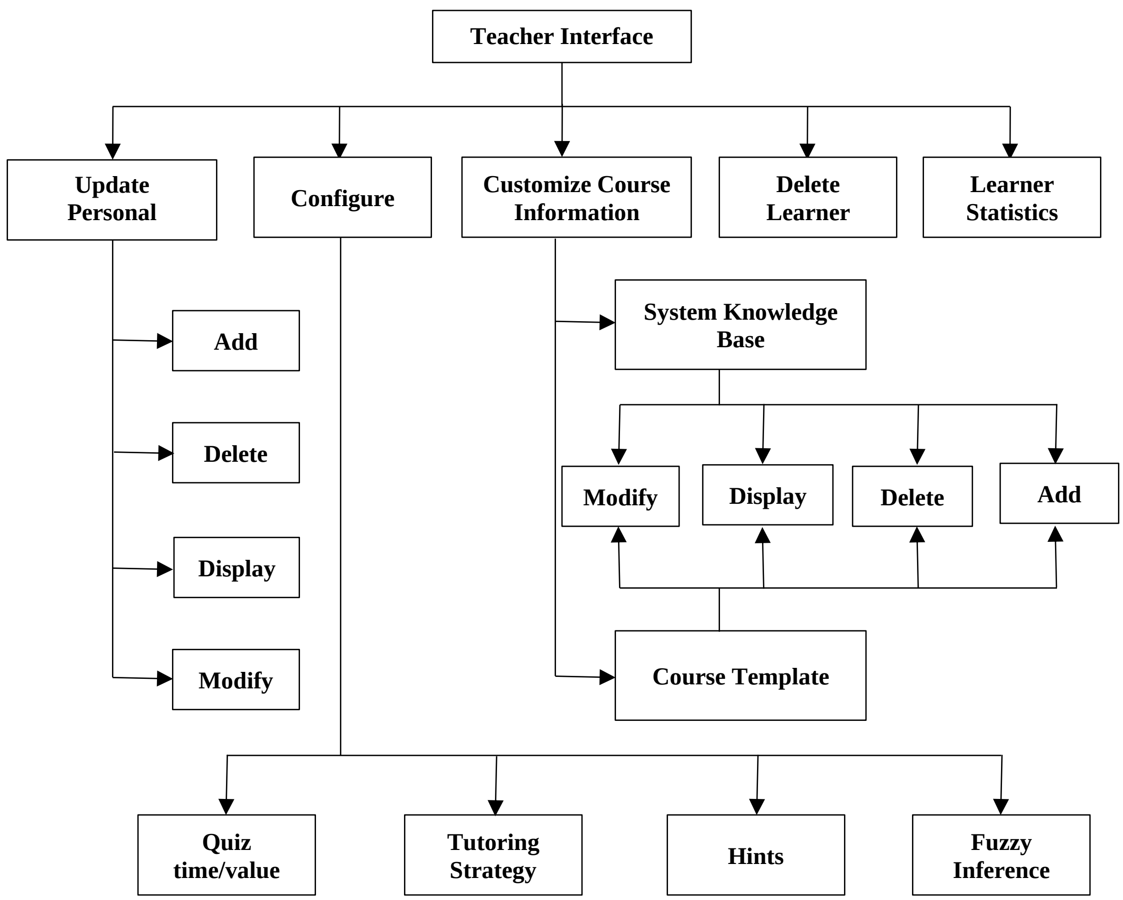


Figure - 6.19: The Organization of the Teacher Interface Model

6.6.1 Update Personal Information

The update personal information control allows the teacher to update the personal information such as name, email, phone number etc. The teacher can add, modify, display, and delete own information.

6.6.2 Configuration Learning Content

This allows the teacher to configure the learning contents, quiz, and hint components of the SeisTutor. The fuzzy inference model has been implemented within the learner model which takes the crisp input values and produces the stereotypes of the learner as output. The fuzzy inference model has three important functions such as *fuzzifyInfo(), defuzzifyinfo(), and classifyinfo()*. The structure of the fuzzy inference model has been represented in Figure 6.20.

```
Function Fuzzy (Input attributes)
{
Fetch info from the file "FuzzyInfo"
Fetch info from the file "FuzzyRules"
fuzzifyinfo();
defuzzifyinfo();
classifyinfo();
}
```

Figure – 6.20: The Structure of the Fuzzy Function

6.6.3 Customize Course Information

This allows the teacher to customize the learning materials, course annotations, and the knowledge base of the tutoring system. The DFD for customize course info has been shown in Figure 6.20.

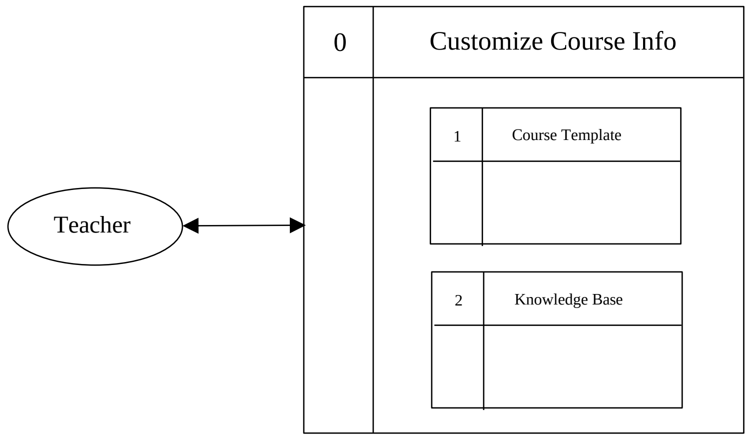


Figure - 6.21: DFD for Customize Course Information

6.6.4 Delete Learner

The learning session information of the learner can be deleted from SeisTutor. The teacher can delete the learner data after completing all the learning sessions from the tutoring system through the teacher interface. Whenever the learner information is deleted, the complete record will delete from the system. Figure 6.22 presents the process of "deleting learner" from the SeisTutor.

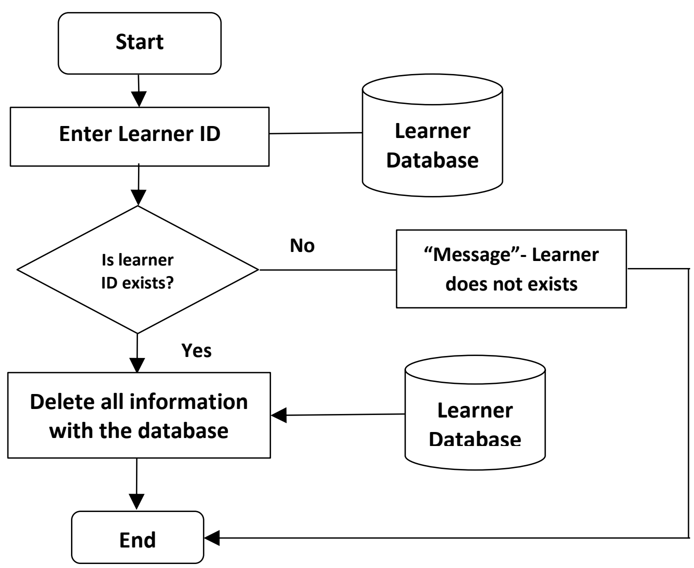


Figure 6.22: The Process of Deleting the Learner

6.6.5 Learner Statistics

The tutoring system maintains two types of data. First, the geographical/background data that provides basic information of the learner such as name, email, age. Second, personalized learning data that is generated during tutoring is used in the system decision making. The system records the learner navigational data during tutoring, and also use the learner personalized data for assessing and evaluating the learner performance. Figure 6.23 presents the learner data charts stored in SeisTutor.

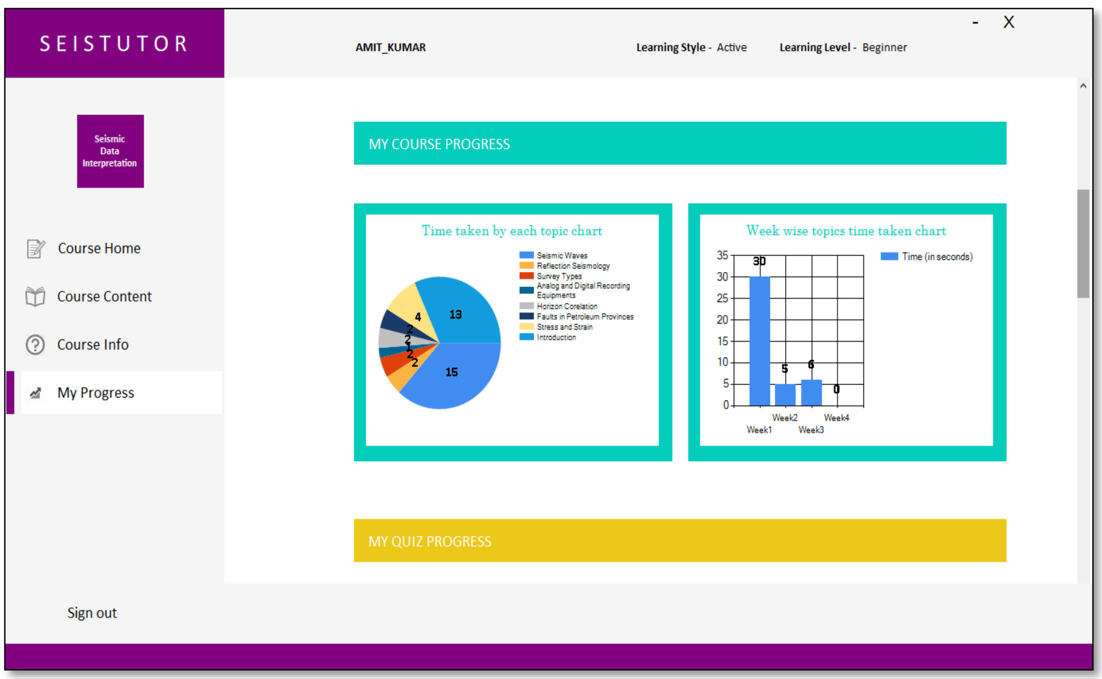


Figure - 6.23: Learning Data Chart Stored with SeisTutor

6.7 LEARNER FEEDBACK QUESTIONNAIRE

The Learner Feedback Questionnaire (LFQ) is used to find the general perception of a learner for SeisTutor. Each learner has to appear for the LFQ, after completion of all the lessons. The LFQ responses have been kept in the 'LFQTextFile'. Table 6.3 presents the organizational structure of ‘LFQTextFile’. The LFQ is presented in Appendix 2 at the end of this thesis.

Table 6.3: The structure of *‘LFQTextFile’*

S.N	Fields	Descriptions
1	Learner ID	The unique id of learner
2	Q1	Learners response to question 1
3	Q2	Learners response to question 2
4	Q3	Learners response to question 3
5	Q4	Learners response to question 4
	. . . . .	. . . . .
	. . . . .	. . . . .
	. . . . .	. . . . .
46	Q46	Learners response of question 44

6.8 SUMMARY

This chapter discusses the design and implementation process of several components and subcomponents of the SeisTutor. SeisTutor is a standalone offline application, implemented with .net framework, fuzzy library, and MS access database. The learner model is developed using the “fuzzy inference rule” which takes the crisp inputs from the system and produces the fuzzy classification which represents the precise stereotypes of the learner. In implementation of the SeisTutor, the tutoring and tutoring strategy model are based on the generic fuzzy rules. The implementation of the learner and teacher interface is explored, learner interface helps the learner to provide the lesson explanations, lesson revisions, quizzes, hints, and the learner feedback. The teacher interface permits to configure the tutoring strategy, lesson, quiz, and hint model. The teacher can add, update or modify the structure of the learning contents. The DFD and screenshots of various components of the SeisTutor also have been shown.

In the following chapter, the results and findings through the evaluation of SeisTutor will be discussed. The analysis of results and the learner perception for the SeisTutor using the learner feedback questionnaire will be discussed.

CHAPTER 7: RESULTS AND DISCUSSION

This chapter describes the evaluation and process of evaluation of the developed prototype – SeisTutor. Analysis of the results of evaluation of learner's performance during tutoring through SeisTutor has presented. The results will be utilized for the recommendation of the appropriate tutoring strategy, changing tutoring strategy, and for the design methodologies of the developed prototype model.

7.1 BACKGROUND

The SeisTutor evaluation procedure is a significant aspect of the tutoring framework as it demonstrates the impact of instruction of an ITS on the learners. The progression of assessments has been accompanied by the learners for testing the adequacy and dependability of the ITS in the real-time situation. The students who participated in the assessment procedure belonged to seismic background, studying at the Indian university and interested to undergo a course on Seismic Data Interpretation (SDI). The data generated in pre-tutoring, post-tutoring, and tutoring phases has been used for the analysis purpose, which is collected from the student's back-end database to evaluate the effectiveness of the SeisTutor.

The study involved four main phases which are

1. Pre-Tutoring Phase
2. Tutoring Phase
3. Post Tutoring Phase
4. Learners Feedback Questionnaire(LFQ) Phase

Each participant has allotted an individual computer with a fully functional installed application (i.e. SeisTutor) in the controlled environment. The process followed in the evaluation of SeisTutor shown below in Figure 7.1.

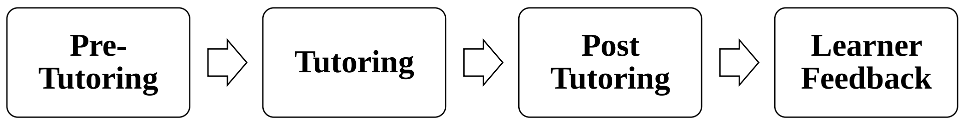


Figure 7.1 - SeisTutor Evaluation Process

Additionally, towards the end of the learning procedure, a Learner Feedback Questionnaire (LFQ) has administered to gather the learner's views on the 'SeisTutor'. The LFQ is presented in Appendix B at the end of this thesis. Additionally, during ongoing tutoring, the data generated and recorded in the learner database has been used to measure the effectiveness of the implemented tutoring strategies in the real-time learning setup.

7.2 EXPERIMENTAL DESIGN

There are 53 participants included in study to evaluate the SeisTutor. The participants were administered tutoring through SeisTutor in a self-paced manner. General data about the gender, age- group, learner type, subject area/field, learner level and inspiration for studying the course is presented in Table 7.1.

Table 7.1 - General Data of Learner for the Experiment

General attributes	Type	Numbers
Gender	Male	37
	Female	16
Age Group	Eighteen and below 18	7
	Above eighteen and below 20	15

	Twenty or above	31
Learner Type	Students	30
	Teachers/Educators	10
	Students and Teachers both	8
	Industrialists/Professionals	5
Subject Area/Field	Computer Science Engineering	6
	Geo Science	36
	Petroleum Engineering and Earth Science	4
	Others	7
Learners Academic Level	Under Graduate Level	30
	Graduate Level	5
	Post Graduate Level	12
	Doctorate Level	6
Inspiration for study	To gain knowledge	
	To experience such a type of tutoring system	
	To get tutoring experience as per their learning style	

7.3 EVALUATIONS

The overall evaluation process has been carried out and divided into two parts

1. Evaluation and analyzing the result of learner's performance during tutoring through SeisTutor
2. Evaluation of the prototype system- 'SeisTutor'.

7.3.1 Evaluation of Learner Performance

One of the objectives, under present research work, is to assess the effectiveness of the system to provide adaptivity, personalization and contribute towards the provision of tutoring of subject matter or Seismic Data Interpretation (SDI). Thus, to evaluate the effectiveness and reliability of the system, the evaluation process involving 53 participants, under a real-time experimental setup was undertaken. In this experiment, learners were offered to study the domain of Seismic Data Interpretation. The fully functional SeisTutor comprises training materials organized as topics/sub-topics/lessons and quizzes, including various components such as, Learner Classification Module, Performance Analysis Module, Tutoring Strategy Selection Module, and Tutoring Strategy Filliping Module, all implemented through various soft computing/AI algorithms.

The evaluation has been conducted on students, academicians of an anonymous university, and industry professionals. While 67% of participants were from ‘Geo-Science/Seismic’ background, 33% were from other engineering backgrounds. Subsequent evaluation has also been carried out on industry practitioners, dealing with the seismic exploration and related disciplines. The four phases have been discussed in the next sections respectively.

7.3.1.1 Pre-Tutoring Phase

Does one shoe fit all? No, it does not! “Same kind of tutoring for all learners” does not either! During its Pre-Tutoring phase, SeisTutor attempts sufficient understanding of learner through its tests, in terms of their preferred learning style and competency level. The Pre-Tutoring phase incorporates two Pre-Tutoring tests i.e. Domain Knowledge Test (DKT) and Learning Style Test (LST). These tests are utilized to assess the student's past information on the Domain (Seismic Data Interpretation) and recognize the learning inclination of students. These tests are used to initiate the tutoring process and are mandatory for all learners, interested to get tutored through SeisTutor. A specific combination of a learning style and competency level is offered as an exclusive tutoring strategy, which is executed in controlled and monitored learning environment. The idea is to model each learner, to offer learner-centric tutoring aimed at superior learning experience.

Domain Knowledge Test (DKT)

The DKT is designed to measure the learner’s competency level of the Seismic Data Interpretation. The primary aim of this test is to classify the learners under learning levels (Beginner, Intermediate, or Expert) based on their scores in the test. The DKT consists of multiple-choice questions and no time limits to complete the test.

Learning Style Test (LST)

The I^2A^2 learning style model (refer Section 4) has been developed to identify the learning style and learning preference of the learner. After identification of learning style of the learner, a tutoring strategy is assigned to the learner.

7.3.1.2 Tutoring Phase

Tutoring phase begins after the pre-tutoring phase. The entire course is divided into lessons and quizzes and is scheduled in different learning sessions. The learner has provided the personalized tutoring strategy according to the profile created in the pre-tutoring phase. Subsequently, the tutoring process initiates through offered tutoring strategy, and all the learning data is recorded and save on the learner database.

7.3.1.3 Post Tutoring Phase

The post-tutoring phase includes the post-tutoring test, which is the final examination consisting of multiple-choice questions from the domain of SDI. The post-tutoring test is designed to test the learner's knowledge and assessing learning after completion of the entire course through the developed system - SeisTutor. The learning data of each learner is collected during the tutoring sessions and evaluation periods. The scores of each learner of both the tests (Pre and Post tutoring) is compared and evaluated. Scoring higher in the post-tutoring test is indicative of gain of the student due to learning experience through developed tutoring system.

The Analysis of Variance (ANOVA) statistical test is viewed as a proper test for making a decision about the importance of sample means or for passing judgment on the critical differences between the two samples (i.e. pre-tutoring test and the post-tutoring test). The ANOVA test has been utilized to compare 2 populations that you have two samples of perceptions being matched together (e.g., learners' test results before and after a specific course). The main objective of the test is to determine whether the SeisTutor is responsible for enhancements in learners' learning/aptitudes (i.e. test results). The applicable test insights of F-proportion has been determined from the example information and afterward contrasted and the worth dependent on F-appropriation (can read from the F-table for the different level of significance for different degree of freedom).

Detailing the procedure, the two estimates of population variance viz., one is based on between samples variance and the other based on within samples variance. Then the said two estimates of population variance are compared with *F*-ratio, wherein we work out.

$$F = \frac{\text{Estimate of population variance based on between samples variance}}{\text{Estimate of population variance based on within samples variance}}$$

7.3.2 Evaluation of Prototype System- SeisTutor

SeisTutor is evaluated through the Learner Feedback Questionnaire (LFQ).

7.3.2.1 Learner Feedback Questionnaire (LFQ) Phase

The Learner feedback Questionnaire has been use to evaluate the effectiveness of SeisTutor in terms of adaptability, personalization, and the learner’s perception of the system. This questionnaire consists of 46 questions concerning the learner’s experience during interaction with the system. Five inquiry reactions or freestyle reactions are incorporated into every one of the questions of the questionnaire. The scale of score of, responses ranges from strongly satisfied (1) to strongly dissatisfied (5). The learners are additionally urged to give freestyle reactions to express interaction with SeisTutor. The questionnaire is presented in Appendix B at the end of the thesis.

7.4 FINDINGS: EVALUATION OF LEARNER PERFORMANCE

The following sections discuss the findings based on the results of the experiment.

7.4.1 Fuzzy Inference Model and Results

The Learner Classification Model and Learner Adaptation Model have been implemented through a fuzzy inference mechanism. The learner classification model categorizes the learner into groups and the adaptation model computes the performance of learners, after tutoring being offered as per learner preference. The following section discusses the results and analysis of the above-stated model.

7.4.1.1 Results and Analysis of Learner Classification Model

The results for the learner classification model are presented in this section. The scores for the pre-tutoring tests were used to classify the learners into groups. The Min-Max normalization technique (Refer Section 6.4.4.3) has been used to normalize the pre-tutoring tests scores. The process of normalization using linear transformation of the original scores to fit the score in the range of [0.0, 10.0] has been done. Hence, data range uniformity is maintained for further processing. The following Table 7.2 presents the data of the pre-tutoring tests of 53 learners that are obtained for process of learner classification.

Table 7.2 – Classification of Learner's based on the DKT scores and LST parameter scores

S.N.	Observed Values (scores out of 20)					Normalized Values (scores out of 10)					Classified Groups (Fuzzy Classification)
	DKT Score	LS Parameters Score				DKT Score	LS Parameters Score				
	LL	IMG	INU	ACO	ACT	LL	IMG	INU	ACO	ACT	
L1	7	13	7	6	11	3.5	7.22	3.89	3.33	6.11	G_5
L2	6	8	9	12	14	3	4.44	5	6.67	7.78	G_4
L3	9	13	10	14	9	4.5	7.22	5.56	7.78	5	G_7
L4	5	15	8	11	13	2.5	8.33	4.44	6.11	7.22	G_1
L5	9	17	15	11	7	4.5	9.44	8.33	6.11	3.89	G_5
L6	3	8	11	10	13	1.5	4.44	6.11	5.56	7.22	G_4
L7	8	16	8	11	6	4	8.89	4.44	6.11	3.33	G_5
L8	12	8	11	12	15	6	4.44	6.11	6.67	8.33	G_8
L9	11	12	11	11	8	5.5	6.67	6.11	6.11	4.44	G_5
L10	14	15	8	11	13	7	8.33	4.44	6.11	7.22	G_5
L11	7	12	5	4	10	3.5	6.67	2.78	2.22	5.56	G_5
L12	5	10	13	15	7	2.5	5.56	7.22	8.33	3.89	G_3
L13	6	13	5	12	17	3	7.22	2.78	6.67	9.44	G_4
L14	3	16	13	10	8	1.5	8.89	7.22	5.56	4.44	G_1
L15	12	14	9	12	7	6	7.78	5	6.67	3.89	G_5
L16	8	13	11	10	6	4	7.22	6.11	5.56	3.33	G_5
L17	5	6	9	10	14	2.5	3.33	5	5.56	7.78	G_4
L18	6	16	7	11	13	3	8.89	3.89	6.11	7.22	G_5
L19	5	5	15	11	8	2.5	2.78	8.33	6.11	4.44	G_6
L20	8	14	8	10	9	4	7.78	4.44	5.56	5	G_5
L21	7	12	11	9	15	3.5	6.67	6.11	5.00	8.33	G_8
L22	4	11	7	12	10	2	6.11	3.89	6.67	5.56	G_3
L23	7	11	7	7	9	3.5	6.11	3.89	3.89	5	G_5
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L53	7	11	15	10	12	3.5	6.11	8.33	5.56	6.67	G_6

According to the collected sample data of learner performance, the mean score of DKT was observed as [3.60], mean score of IMG as [6.67], mean score of ACO as [5.24], mean score of INU as [5.80], and mean score of ACT as [5.85] as shown in Figure 7.2 below. Finally, as a result of this process, all participants have been categorized as per their knowledge level and learning styles.

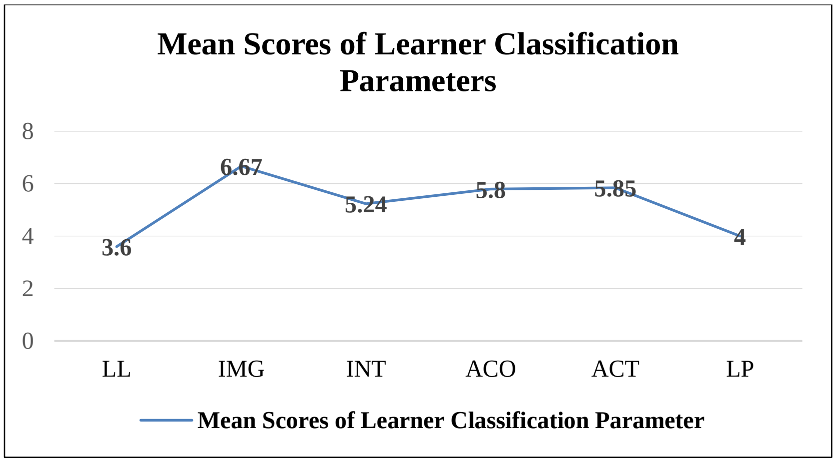

Figure 7.2 – Mean Score of Learner Classification Parameters

The functionality of modules, such as, the learner model, its sub-models and the tutoring strategy model are tested. The outputs of the learner model are compared with the output of the fuzzy inference simulation through MATLAB 2014a model and both of the output were found to be identical. The Mamdani fuzzy inference approach has been used for the classification of a learner. The triangular membership function has been used in the proposed model for the five input parameters or linguistic variables, which are learner level, imagistic, intuitive, acoustic and active and one output variable i.e. learner profile as shown in Figure 7.2. Each of the fuzzy input variables has three membership functions each. The output variable has 12 membership functions. As a result of the 5 linguistic variable set, each having three classes, 243 rules with their conditions have been formulated.

7.4.1.2 Results and Analysis of Learner Adaptation Model

The Learner Adaptation Model presents the learner performance during the learning process. The Min-Max normalization technique (refer Section 7.4.4.3) has been used to normalize the performance scores. Three performance parameters have been used in the present study: Correct Response (CR), Hint Taken (HT), and Time Taken (TT). The process of normalization using linear transformation of original scores to fit the score in the range of [0.0, 10.0] has been done. Hence, data range uniformity is maintained for further processing. The following Table 7.3 presents, the sample measures of learner performance of week-1 for 53 learners.

Table 7.3 – Performance of Learner: Analysis of Week1

S.N.	Observed Values (out of 5)			Normalized Values (out of 10)				Learner's Fuzzy Performance Values (LFPV)
	Performance Parameter			Performance Parameter				
	Correct Response	Hint Taken	Time Taken (in Seconds)	Correct Response	Hint Taken	Threshold Time Value	Normalized Time Value	
L1	3	0	200	6	0	200	6.67	5.99
L2	1	3	230	2	6	230	7.67	7
L3	1	0	219	2	0	219	7.3	7
L4	2	0	185	4	0	185	6.17	5
L5	3	0	287	6	0	287	9.57	4.21
L6	4	1	245	8	2	245	8.17	7
L7	3	0	199	6	0	199	6.63	5.99
L8	2	4	289	4	8	289	9.63	5
L9	5	3	390	10	6	300	10	7
L10	3	2	176	6	4	176	5.87	6
L11	1	0	323	2	0	300	10	1.53
L12	4	2	278	8	4	278	9.27	5
L13	2	2	345	4	4	300	10	9.37
L14	3	1	298	6	2	298	9.93	4.31
L15	3	1	287	6	2	287	9.57	4.31
L16	4	2	267	8	4	267	8.9	5.2
L17	3	0	285	6	0	285	9.5	7
L18	4	3	328	8	6	300	10	5
L19	3	1	327	6	2	300	10	6
L20	2	0	369	4	0	300	10	1.54

L21	2	0	274	4	0	274	9.13	1.54
L22	3	1	238	6	2	238	7.93	6
L23	3	1	213	6	2	213	7.1	6
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L53	3	1	389	6	2	300	10	4.31

The performance of learner for week-1 has been analyzed using the fuzzy inference technique as shown in Table 7.3. Similarly, the score of performance of learner in week-2, week-3, and week-4 have been computed and analyzed as shown in Table 7.4.

Table 7.4 – Overall performance analysis of learner

S.N	Before Tutoring		During Tutoring				After Tutoring		% increment (Pre to Post Tutoring)
	Pre Tutoring Score	Learner Level (LL)	Week wise learner performance				Post Tutoring Score	Learner Level (LL)	
			W1	W2	W3	W4			
L1	3.5	INT	5	5	7.5	9.12	8	EXP	128.57
L2	3	BEG	1.53	5	9.12	7.5	8.5	EXP	183.33
L3	4.5	INT	1.53	6.61	5.31	5	8.5	EXP	88.89
L4	2.5	BEG	5	5.87	5	9.18	5.5	INT	120
L5	4.5	INT	5	7.5	7.5	9.12	8	EXP	77.78
L6	1.5	BEG	9.12	9.12	5	9.12	6	INT	300
L7	4	INT	5	5	9.12	9.18	9	EXP	125
L8	6	INT	1.53	7.5	8.1	9.24	5.5	INT	-8.33
L9	5.5	INT	7.5	9.18	9.18	9.12	8.5	EXP	54.55
L10	7	EXP	5.26	7.5	5	7.5	6.5	INT	-7.14
L11	3.5	INT	1.53	5	7.8	9.18	10	EXP	185.71
L12	2.5	BEG	7.5	9.12	9.12	7.5	9.5	EXP	280
L13	3	BEG	1.3	5	7.5	8.1	7.5	EXP	150
L14	1.5	BEG	5	5	5	9.12	8.5	EXP	466.67
L15	6	INT	5	5	9.12	9.12	8.5	EXP	41.67
L16	4	INT	7.68	9.35	9.12	9.35	7.5	EXP	87.5
L17	2.5	BEG	5	9.12	7.5	9.2	8.5	EXP	240

L18	3	BEG	7.5	7.5	9.18	9.12	7.5	EXP	150
L19	2.5	BEG	5	7.5	7.5	5	9	EXP	260
L20	4	INT	1.3	5	8.48	5	8.5	EXP	112.5
L21	3.5	INT	1.48	7.13	5	9.12	9	EXP	157.14
L22	2	BEG	5	5	5	9.12	6	INT	200
L23	3.5	INT	5	5	9.12	5	8.5	EXP	142.86
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.				.					.
L53	3.5	INT	5	7.5	7.5	7.5	7.5	EXP	114.29
Avg.	3.72						7.94		149.42

The mean score performance of week-1 is [5.19], week-2 is [6.68], Week-3 is [7.27], and week-4 is [7.79] as shown in the Figure 7.3. The performance graphs of learners of week-1, week-2, week-3, and week-4 are presented in Figure 7.4, Figure 7.5, Figure 7.6, and Figure 7.7 respectively.

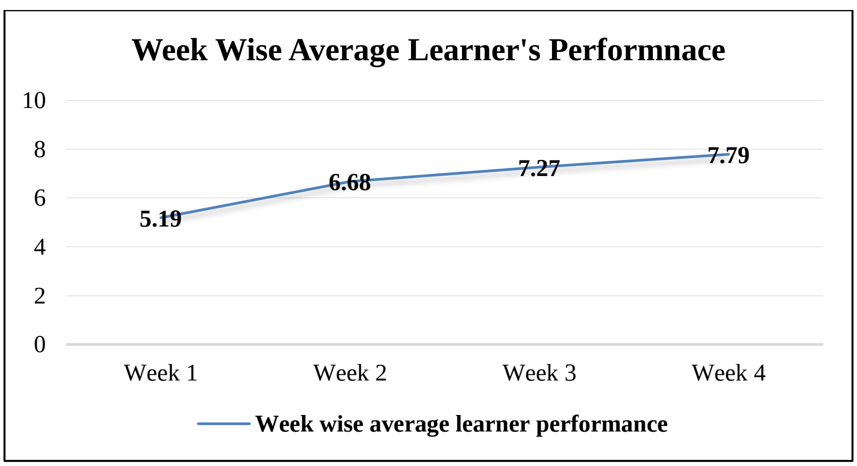

Figure 7.3 – Overall Performance of Learners

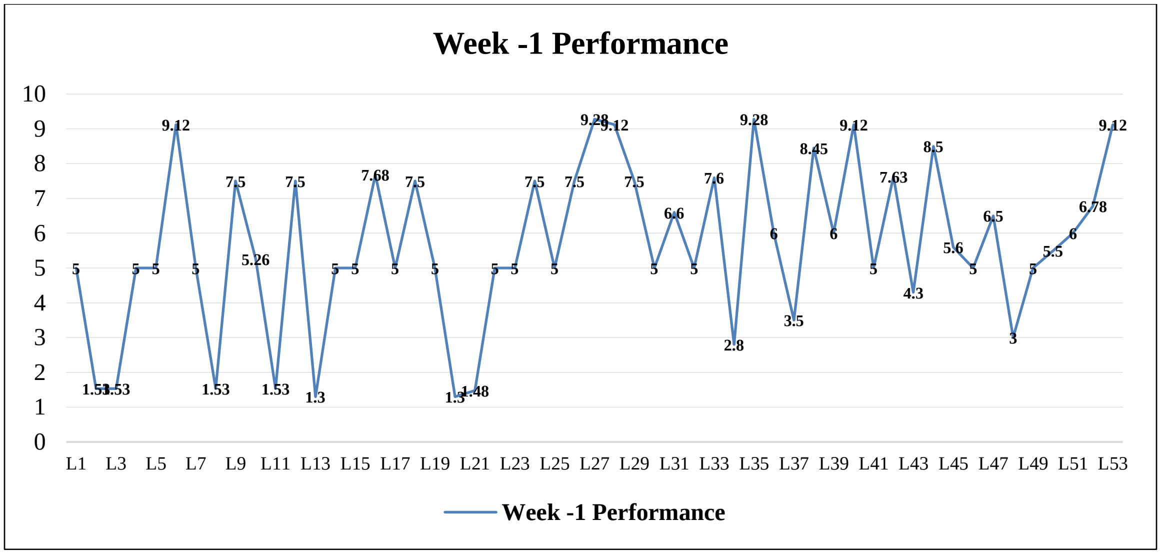

Figure 7.4 – Performance of Learners: Week 1

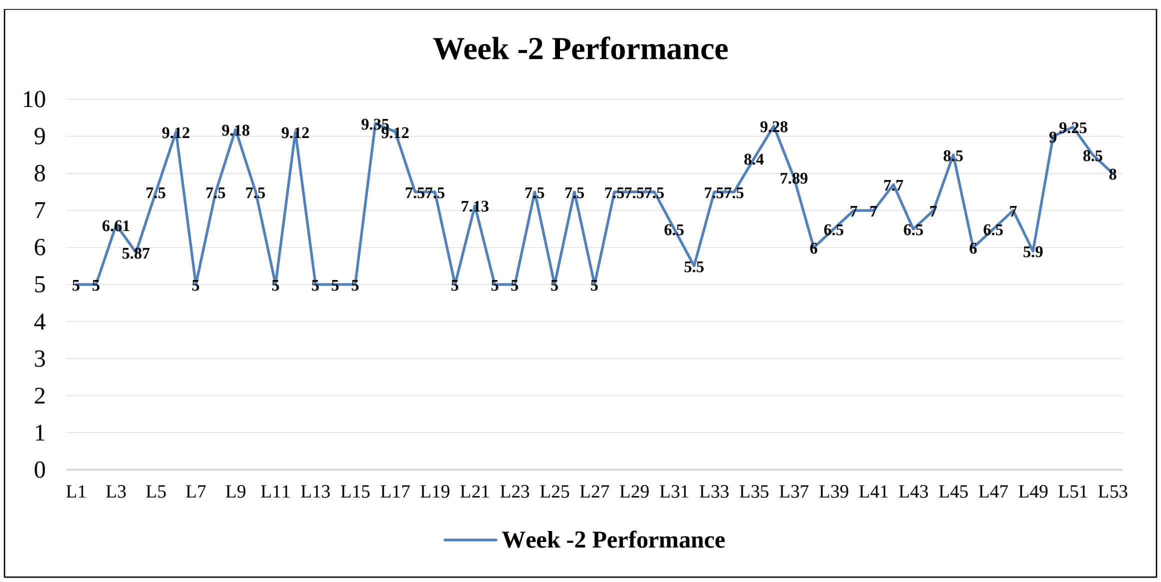

Figure 7.5- Performance of Learners: Week 2

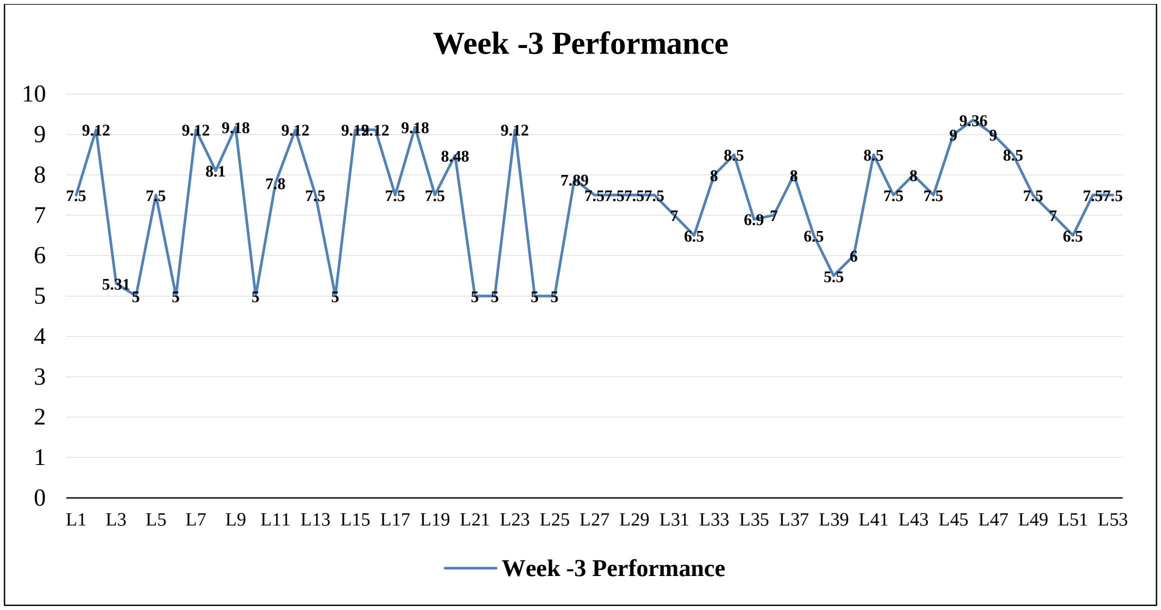

Figure 7.6- Performance of Learners: Week 3

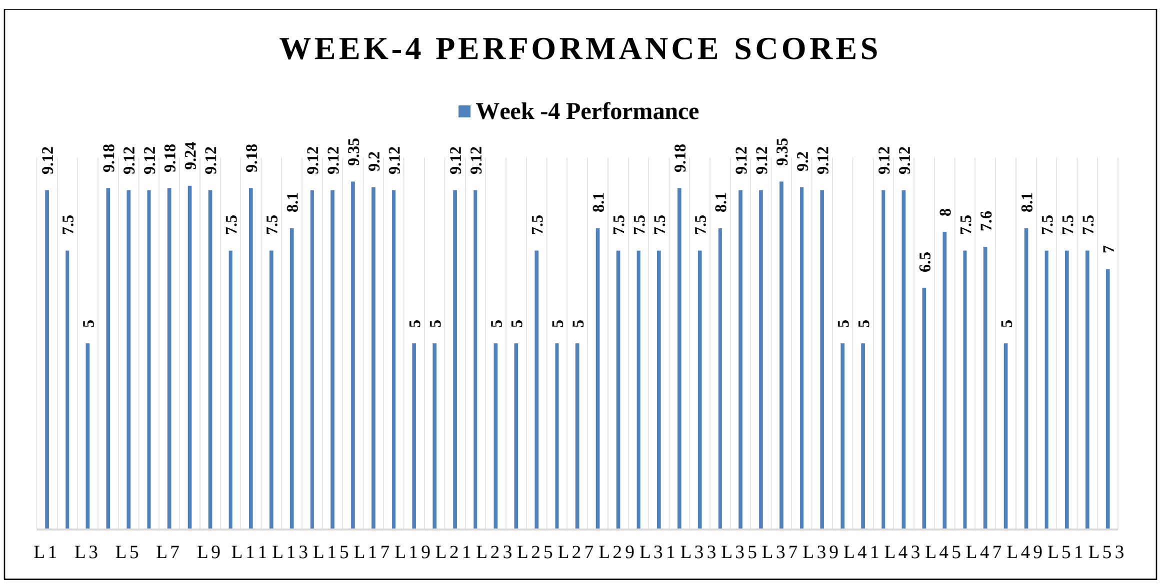

Figure 7.7- Performance of Learners: Week 4

The overall performance results of learners evaluated and analyzed are presented in Table 7.3. SeisTutor has categorizes the learners into three groups i.e. 'Beginner', 'Intermediate', and 'Expert' based on the performance of pre-tutoring tests (see Section 7.2). Considering the pre-tutoring scores of DKT, 21 learners (39.62%) were allotted beginner learner level, 29 learners (58.72%) were allotted the intermediate learner level, and rest of the learners (5.66%) were allotted the expert learner level.

SeisTutor begins the tutoring according to the profile assigned to the learner. The overall tutoring sessions have been organized into four weeks. The performance of learner is recorded and evaluated week wise. Considering the learners that were allotted beginner category, performance results show that none of them are in beginner category any more after undergoing all tutoring sessions. This has been observed that out of 21 learners, 3 learners have scored, within the range of intermediate category and 18 learners have scored within the range of expert category and therefore have upgraded their previous 'beginner' profile, indicating learning gain after undergoing tutoring with the SeisTutor. Table 7.5 presents comparison of learner performance before and after tutoring.

Table 7.5 – Migration between Learner Levels before Tutoring and after Tutoring

S.N	Before Tutoring		After Tutoring		
	Learner Level	**Learners**	**Beginner**	**Intermediate**	**Expert**
1.	Beginner	21	0	3	18
2.	Intermediate	29	0	3	26
3.	Expert	3	0	0	3

Similarly, considering the learners allotted intermediate category, performance results showed their upgrade to the expert category after undergoing tutoring sessions. This has been observed that out of 29 learners, 26 learners have upgraded to expert level and remaining 3 learners remained in the same leaning level but showed improved scores.

Finally, there was only one learner allotted expert level, who remained in the same level after tutoring but showed improved score.

Therefore, this can be concluded from the results analysis, learners improved their performance in terms of score and achieved higher learning satisfaction level. The following charts show learners upgrade to higher learning levels after tutoring. Figure 7.8 and Figure 7.9 presents comparison of the learner data before tutoring and after tutoring commences in terms of their learning levels.

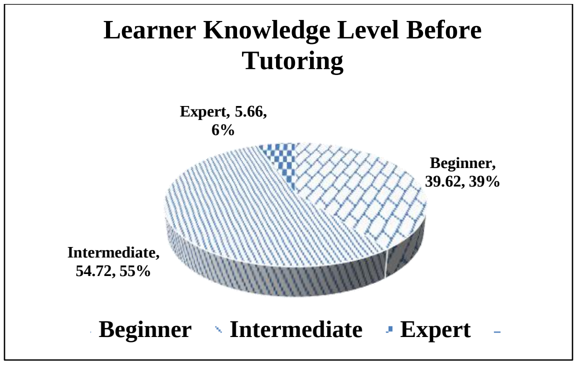

Figure 7.8 – Learner Knowledge Level before Tutoring

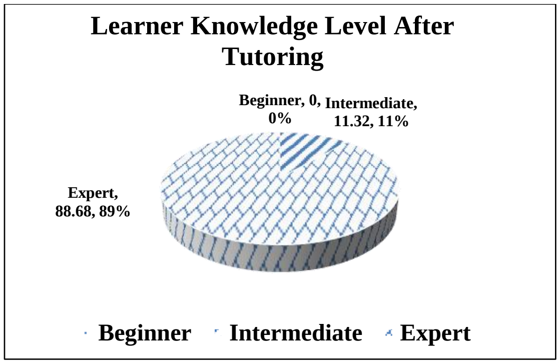

Figure 7.9 – Learner Knowledge after Tutoring with SeisTutor

7.4.1.3 Estimation of Tutoring Strategy (TS) Results and Analysis

The results of the tutoring strategies assigned to the learners are discussed and analyzed for each learning session (week wise) in terms of their final performance. This section analyzes the suitability of the assigned TS as per individual needs. As discussed, the changing rule of the tutoring strategy (refer Section 3.) and Table 7.3 includes the learner performance results of week-1 using fuzzy inference technique (see Section 7.3.1.2). Figure 7.11 shows the performance results of learners of week -1. The fuzzy scores are considered for evaluating the adaptability and personalization of tutoring system.

Analyzing the results of week-1 (see Table 7.3), learners L2, L3, L8, L11, L13, L20, L21, L34, L37, L43, and L48 have score less than the threshold value and decision has been to change the tutoring strategy for the forthcoming tutoring sessions. The following Table 7.6

presents the learner performance through score data for learners with poor performance in week-1 and decided to change the tutoring strategy for successive tutoring sessions.

Table 7.6 – Analysis of performance data of learners who changed their TS

Learners	Before Tutoring		During Tutoring				After Tutoring	
	Pre Tutoring Score	Learner Level (LL)	Week wise result				Post Tutoring Score	Learner Level (LL)
			W1	W2	W3	W4		
L2	3	BEG	1.53	5.0	9.12	7.5	8.5	EXP
L3	4.5	INT	1.53	6.61	5.13	5	8.5	EXP
L8	6	INT	1.53	7.5	8.1	9.24	5.5	INT
L11	3.5	INT	1.53	5.0	7.8	9.18	10	EXP
L13	3	BEG	1.3	5.0	7.5	8.1	7.5	EXP
L20	4	INT	1.3	7.5	8.48	5	8.5	EXP
L21	5	INT	1.48	7.13	5	9.12	9.0	EXP
L34	2.5	BEG	2.8	7.5	8.5	8.1	8.5	EXP
L37	3	BEG	3.5	7.89	8	9.35	7.5	EXP
L43	3	BEG	4.3	6.5	8	9.12	8.5	EXP
L48	3.5	INT	3	7	8.5	7.6	8	EXP

Analyzing the results of 11 learners, 5 learners allotted beginner level and 6 learners intermediate level. SeisTutor evaluates and analyzes the performance of week-1 and intelligently suggests changing the tutoring strategy for the learners. All the learners changed their tutoring strategy and resumed learning for the successive learning session. The results shown in Table 7.5 reveal that the learners improved their performance in week-2 and in successive weeks. This is evidenced from the improved scores in successive weeks that the tutoring strategy suggested has been effective and adaptable to the learner's need and preferences.

The following Table 7.7 presents the performance results of learners as per their decisions to exercise their choice to change TS or continue with existing TS.

Table 7.7 – Analysis of change of TS results

S.N.	Features	
1.	Numbers of learner's who change the tutoring strategy	11
2.	Numbers of learner's who did not change the tutoring strategy	42
3	Total percentage of students who were happy with assigned TS (Personalization)	79.25%

As a result presented in Table 7.6, out of 53 learners that participated for system evaluation. Considering the performance scores of week-1, 42 learners have not changed the tutoring strategy assigned to them, and such tutoring strategy is termed as personalized tutoring strategy. 42 (79.25%) learners out of 53 were satisfied with the assigned tutoring strategy, this has appeared in terms of achieving a high score. These 11 learners decided to change the tutoring strategy as a system triggered to change tutoring strategy due to the weak performance in week-1. Figure 7.10 presents the week-1 performance of learners before changing tutoring strategy. Therefore, once they commit to change the tutoring strategy, a new tutoring strategy generated and is assigned to them. Thus, it has been observed that learners have improved their scores in the performance of week-2 and in the successive learning sessions. Figure 7.11 presents the performance of week-2 in terms of the high score after assigning new tutoring strategy to them. Figure 7.12 and Figure 7.13 presents the performance of week-3 and week-4. It has been seen that learners improved their performance in the lessons of successive weeks and they were adapting the learning content. Consequently, we can say that the tutoring strategy was adaptive during learning sessions and learners were satisfied with the new tutoring strategy assigned to them.

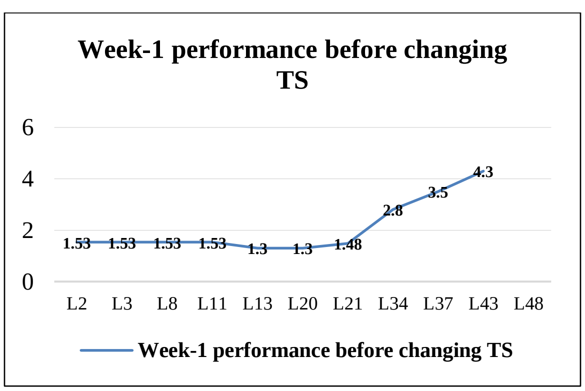

Figure 7.10 – Week-1 Performance before Changing TS

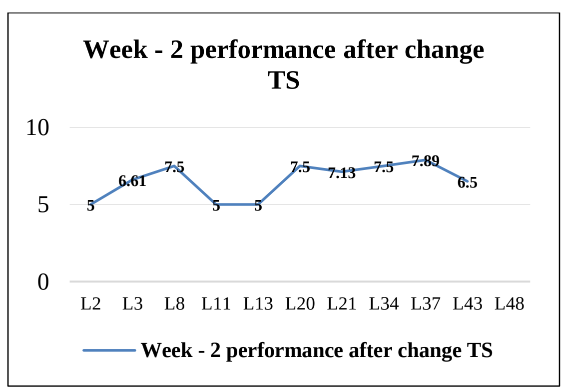

Figure 7.11 – Week-2 Performance after Changed TS

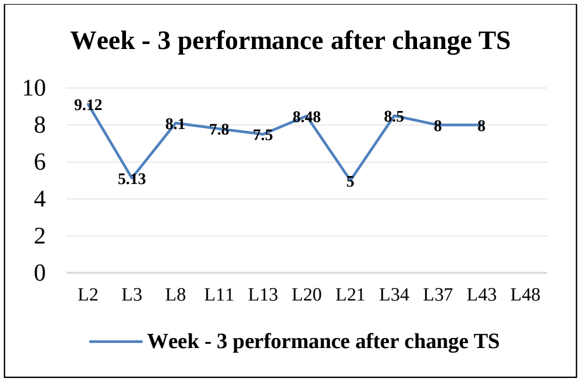

Figure 7.12 – Week-3 Performance after Changed TS

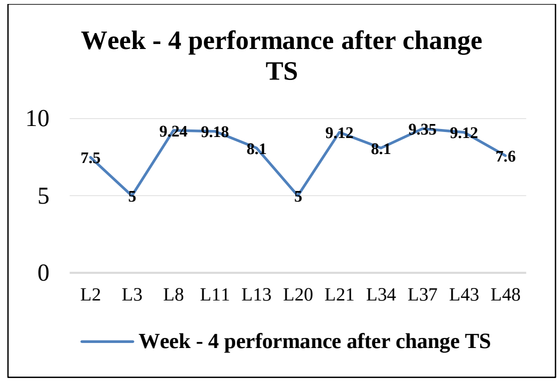

Figure 7.13 – Week-4 Performance after Changed TS

7.4.2 Results and Analysis of Learners Engagement with SeisTutor

The evaluation of a system is essential, as it is serves to decide the future usability of a given product (Phillips and Gilding, 2003). According to Mulwa et al. (2011), there is no clear guideline or an agreed metric to assess the effectiveness of a system or guideline with respect to adoption for an adaptive intelligent tutoring system. The principal aim of this experiment is to assess the effectiveness of the system.

7.4.2.1 Findings from Evaluation of SeisTutor

Evaluation of SeisTutor showed that most of the learners were engaged during the tutoring session. The time (in minutes) spent by the participants undergoing tutoring with SeisTutor is shown in Table 7.8. The tutoring system contains a total number of 12 lessons and 4 quizzes. The tutoring was conducted in five sessions. Overall aggregate of length of time the participants spent undergoing tutoring was 265 hours. This time has been referred to as ‘engagement’, in this text. The average engagement per participant was 300 minutes per session, and an average learner’s engagement per session was 55 minutes. Higher length of time is indicative of sustained interest and positive impact over the participants.

Table 7.8 – Analysis of learner’s engagement with SeisTutor

Engagement	**Total time**
The total engagement of all learners	265 hours
The average engagement per learner with the system	300 minutes
The average learner’s engagement per session	55 minutes

Time spent on studying the lesson with the system is calculated week wise and lesson wise. The Table 7.9 shows the time spent to complete the course, lesson wise as well as week wise.

Table 7.9 - Week wise and lesson wise time spent by learner

S.N.	**Time Taken (In Minutes)**																**Total Time**
	Week Wise				**Lesson Wise**												
	W1	**W2**	**W3**	**W4**	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**	**L8**	**L9**	**L10**	**L11**	**L12**	**237**
L1	58	76	49	54	22	19	17	21	25	30	16	17	16	21	18	15	**230**
L2	67	57	57	49	19	23	25	20	16	21	15	18	24	17	19	13	**237**
L3	64	71	37	65	19	14	31	23	19	29	13	16	8	23	19	23	**220**
L4	49	59	54	58	16	14	19	24	21	14	18	19	17	23	14	21	**227**
L5	58	67	39	63	24	18	16	23	19	25	11	14	14	18	12	33	**245**
L6	55	65	49	76	21	19	15	24	21	20	14	19	16	32	24	20	**226**
L7	45	72	56	53	19	17	9	28	21	23	16	20	20	19	17	17	**242**
L8	47	79	46	70	20	14	13	24	39	16	22	14	10	24	12	34	**227**
L9	49	68	43	67	19	17	13	21	23	24	22	10	11	22	23	22	**224**
L10	44	80	51	49	13	16	15	27	23	30	22	10	19	12	16	21	**222**
L11	57	67	44	54	21	18	18	27	19	21	10	18	16	13	14	27	**243**
L12	58	63	53	69	21	19	18	24	19	20	18	16	19	23	12	34	**228**
L13	54	70	46	58	17	19	18	29	17	24	12	18	16	28	14	16	**258**
L14	55	69	71	63	19	16	20	21	27	21	28	22	21	19	18	26	**236**
L15	67	61	57	51	23	17	27	21	15	25	8	28	21	27	7	17	**236**
L16	73	58	53	52	31	26	16	17	19	22	12	19	22	19	16	17	**230**
L17	69	57	46	58	21	19	29	21	17	19	20	16	10	22	20	16	**236**
L18	79	49	47	61	28	22	29	17	16	16	13	18	16	23	13	25	**224**
L19	55	74	49	46	18	16	21	27	19	28	24	18	7	15	15	16	**224**
L20	48	67	50	59	18	16	14	22	18	27	15	18	17	24	14	21	**238**
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L30	75	49	63	46	29	17	29	18	16	15	17	19	27	12	18	16	**230**
Mean	**58.45**	**65**	**51.58**	**59.39**	**20.52**	**18.06**	**19.87**	**22.81**	**19.87**	**22.32**	**17.23**	**18.19**	**16.16**	**20.90**	**16.84**	**21.69**	**234.42**

The following Figures 7.14 and 7.15 show week wise average time taken and learner performance.

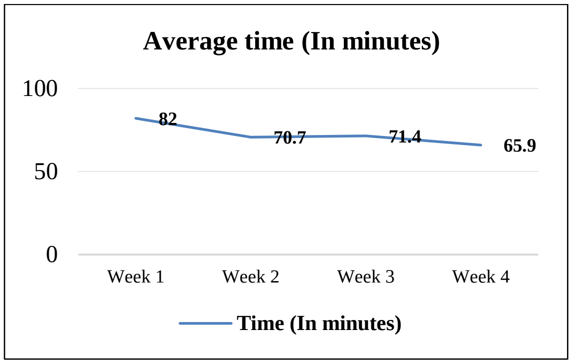

Figure 7.14 – Week Wise Average Time Taken

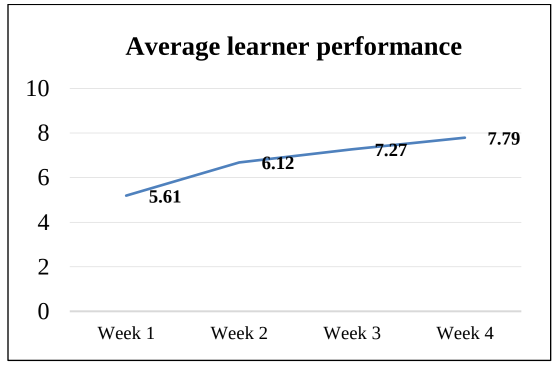

Figure 7.15 – Week Wise Average Performance

The lesson wise average time taken by the participants to complete the lessons is shown in the Figure 7.16 below.

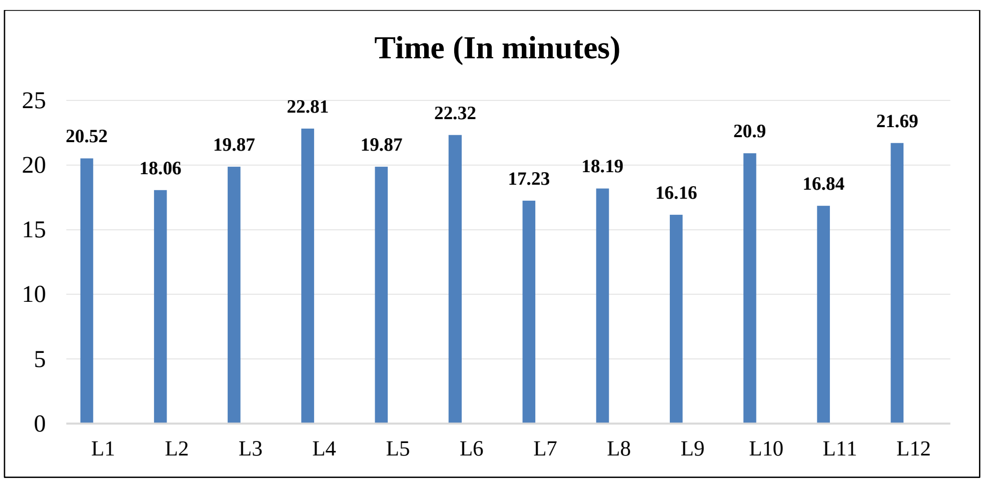

Figure 6.16 - Lesson Wise Average Time Spent with the System

The following Figure 7.17 and Figure 7.18 show distribution of learners as per learner level and learning style respectively. The distribution is presented in the form of percentage.

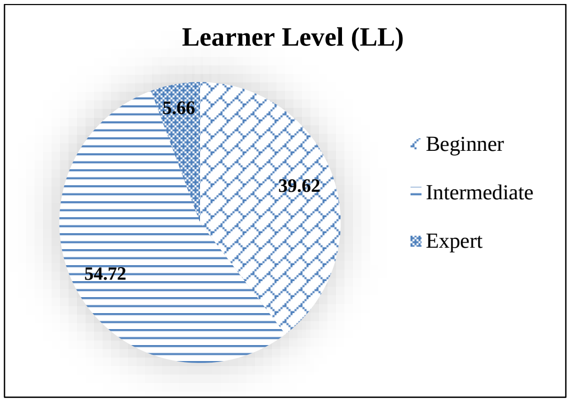

Figure 7.17 – Distribution of Learner Level of Participants

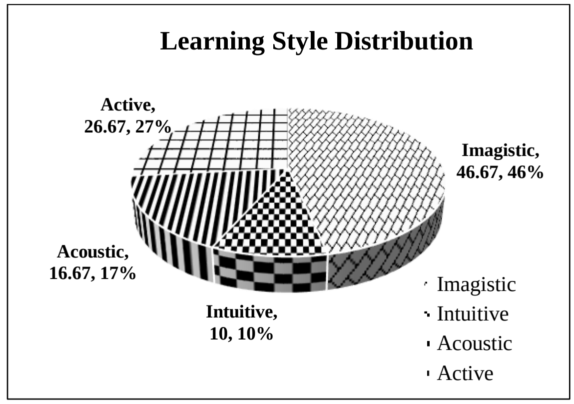

Figure 8.18 – Distribution of Learning Styles of Participants

7.4.3 Results and Analysis of Pre and Post Tutoring Performance

The pre-tutoring and post-tutoring test performance of 53 participants has been computed. The mean score of DKT (Pre-Tutoring test) in this experiment was 3.72 while the mean score, of post-tutoring test was 7.94. These two tests have been elaborated in Section 5. The ANOVA statistical test has been applied on pre-tutoring and post-tutoring scores of participants. The computed value of F-ratio of ANOVA test, $F_{calc} = 327.22$ at $\alpha=0.05$, where α is significant level, while the tabulated value of the F-ratio of ANOVA test, $F_{\alpha} = 243.3$ (as per F-Table). Here $F_{calc} > F_{\alpha}$, hence the null hypothesis H_o is rejected and the alternate hypothesis H_a: $\mu_1 < \mu_2$ is accepted. This indicates that there is a significant difference between pre-tutoring and post-tutoring tests. Hence, we infer that the tutoring is successful and effective with SeisTutor. The mean learning gain has been calculated using the mean score of pre-tutoring test and post-tutoring test. The mean learning gain of the participants is 42.26%. The learning gain is shown in the Table 7.10 below.

Table 7.10 - Data of pre and post tutoring in terms of learning gain

System	Total Participants	Pre-Tutoring Test Score	Post-Tutoring Test Score	Mean Learning Gain
SeisTutor	53	3.72	7.94	42.26%

Table 7.11 - Data of ANOVA Test

Source of variation	**SS**	**DF**	**MS**	**F-ratio**	**5% F-limit (From the F table)**
Between Sample	1893.43	(2-1)=1	1893.43	327.22	F (1, 104) = 243.3
Within Sample	601.78	(106-2)= 104	5.79		
Total	2495.21	(106-1)= 105			

The above Table 7.11 shows that the calculated value of F is 327.22, which is greater than the value of 243.3 at 5% significant level with the degree of freedom being v_1 =1 and v_2 = 104. This analysis do not supports the null hypothesis. It accepts the alternative hypothesis H_a: $\mu_1 < \mu_2$ that indicates a significant difference between the sample means. We may, therefore conclude that the difference in the post-tutoring and pre-tutoring test is significant and training is effective.

7.5 FINDINGS: EVALUATION OF PROTOTYPE SYSTEM- SEISTUTOR

This section discusses the findings by analyzing the results of the perception of SeisTutor by using the tool - Learner Feedback Questionnaire (LFQ).

7.5.1 Learner Feedback Questionnaire (LFQ): Analysis

The analyzed results of learner's feedback questionnaire responses with 53 participants are presented in this section. The LFQ comprises of 46 questions (refer Appendix - B) and the effectiveness of the system is evaluated on pre-identified parameters, as per responses of learners in LFQ. The pre-identified parameters are: System Effectiveness, Adaptability, Personalization, System Support, and Ease-of-use also known as system performance parameters. Figure 7.19 presents the system performance parameters.

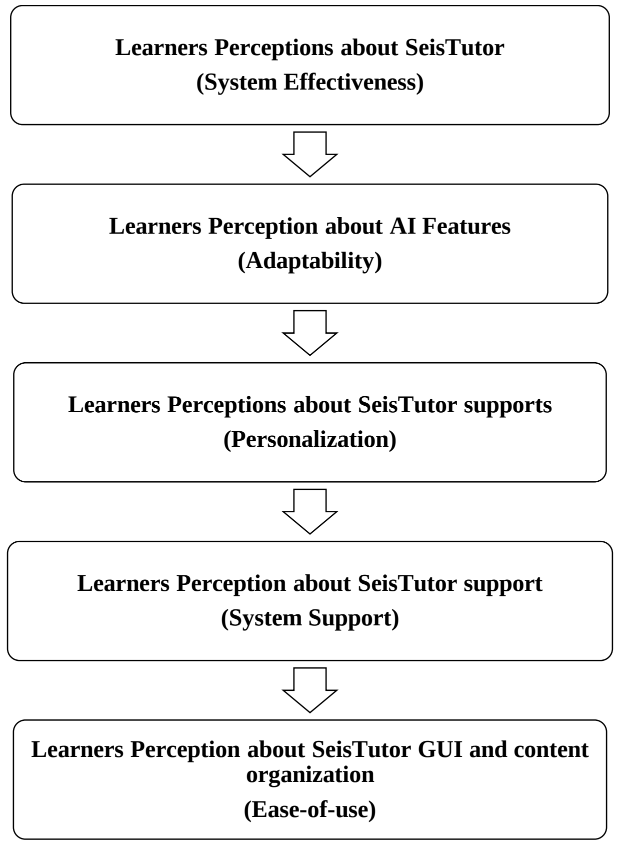

Figure 7.19: SeisTutor Performance Parameter

The LFQ is distributed among the performance parameters. Table 7.12 presents the one to one mapping of LFQ with the system performance parameter: System Effectiveness, Adaptability, Personalization, System Support, and Ease-of-use.

Table 7.12 – One to One Mapping of LFQ with the System Performance Parameters

S.N	Learner Feedback Questionnaire (LFQ)
System Effectiveness	Did the SeisTutor meet your expectation? What is your overall level of satisfaction with SeisTutor? The learning through this tutoring system (SeisTutor) was easy. Did you feel that you were achieving learning outcomes? Did the tutoring system help you to understand the concepts of SDI? I would recommend a course through SeisTutor with no instructor help. Would you recommend SeisTutor to individual who needs to take another course? Did SeisTutor support you to make your study productive? How well does this system deliver on your learning intentions?
Adaptability	Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor? Were you comfortable with the pedagogy flip by the SeisTutor? Did you feel that your performance improved after pedagogy flip? The pre-learning procedure provided by SeisTutor after pedagogy flip was at the right level that you understood. The tutoring session was at the right level of difficulty for me after changing the tutoring strategy. Were the learning contents as per your learning style after pedagogy flip? Did you think, the test provided to you was at the right difficulty level after pedagogy flip? Did the course provide to you at your educational needs? Did you think that when you reach to the next learning level, you had already known all the previous chapters? Did you have the experience to return back to the previous chapters, if you had any errors or doubts int that?
Personalization	Did SeisTutor satisfy you with learner profile identification in real-time of your learning profile? Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor? The information provided by SeisTutor is at a level that you understand. The tutoring session was at the right level of difficulty for me. As a learner, did you feel that your learning style was appropriately judged? Did you think, the test provided to you was at the right difficulty level? Once, tutoring begins and you were tutored, were your learning preferences sufficiently satisfied? Did the experience of learning by your own learning preference, make you perform better?
System Support	How are you satisfied with the system support in terms of presenting lessons, revisions, and assignments? Were the system help to find the intended learning lessons or tests? The system navigation support enabled finding the needed information easily. Was the pre-learning procedure available in SeisTutor helpful to you? Were you able to understand the language used to explain the lessons in SeisTutor? Were you able to understand the language used to explain the tests/exercises in SeisTutor? The tutoring was flexible to meet my learning requirements.
Ease-of-use	Were you able to find the pre-learning procedure you were looking for on our system? Did you find the pre-learning information valuable? How the visually appealing was is our tutoring system application? Were you able to understand the language used to explain the lessons in SeisTutor? How easy to navigate to the SeisTutor to find information? How the pre-tutoring and tutoring session's links were easily available? How satisfied are you with the look and feel (user interface design) of this system? How satisfied are you with the account setup experience of this system? How user-friendly is this system? Give a rating SeisTutor compels and supports me to complete the quizzes and lessons. How satisfied are you with the organization/ customization of contents feature of the system? Were you able to find the pre-learning procedure you were looking for on our system?

7.5.1.1 System Effectiveness

The effectiveness of tutoring system is measured through the performance of learner in terms of their reactions while using the SeisTutor. This has been appeared in their responses recorded in the SeisTutor in terms of getting high score. Whether they would like to recommend the SeisTutor to others who need to take this study, or agreed that they are achieving good score. The responses of the feedback questions mapped to the System Effectiveness is presented in Table 7.13. 86.79% of the learners showed that they would recommend it to others, out of which 50.94% showed strong agreement and the remaining 35.85% agree on recommendation to peers and others as well. The overall satisfaction with SeisTutor was 83.02%, out of which 50.94% were strongly satisfied and 32.07% were satisfied as well. 79.24% of the learners showed that they have achieved higher learning outcomes and learning through SeisTutor was easy, out of which 47.17% were strongly satisfied and 32.10% were satisfied. Therefore, the learners study became productive and easy with the SeisTutor. It has been also observed that considering the parameter "study without instructor", 86.79% of learners would recommend SeisTutor to others.

Table 7.13 – Analysis of responses of Learner feedback questionnaire: System Effectiveness

	Questions	**Degree**				
		Strongly satisfied	**Satisfied**	**Neutral**	**Dissatisfied**	**Strongly dissatisfied**
System Effectiveness	Did the SeisTutor meet your expectation?	23	25	0	2	3
	What is your overall level of satisfaction with SeisTutor?	27	17	4	3	2
	The learning through this tutoring system (SeisTutor) was easy.	25	17	6	3	2
	Did you feel that you were achieving learning outcomes?	23	19	4	4	3
	Did the tutoring system help you to understand the concepts of SDI?	23	24	2	2	2
	I would recommend a course through SeisTutor with no instructor help.	27	19	3	2	2
	Would you recommend SeisTutor to individual who needs to take another course?	24	21	2	1	3
	Did SeisTutor support you to make your study productive?	20	23	6	3	1
	How well does this system deliver on your learning intentions?	21	22	4	4	2

Therefore, by analyzing the results of the responses of the LFQ (refer Appendix B), the learners were very satisfied with the SeisTutor and its contribution to the learning for the domain of SDI. The results with the pre-identified performance parameter as per responses of learner's in LFQ have been presented in Figure 7.20. The results of the evaluation showed that the first performance parameter that is *system effectiveness*, 84.36% of learners considered that they improved learning outcomes tutoring through the SeisTutor. Moreover, considering the *adaptability* features of the system, 85.29% of learners adapt the changing learning conditions in terms of tutoring strategy, and the system adapts the learner behavior automatically according to their needs. Considering the third parameter that is *personalization*, 83.22% of learners were comforted with the tutoring strategy provided and agreed they have improved their performance in terms of the high score. Considering the fourth parameter that is *system support*, 82.45% of learners agreed with the system support in terms of presenting lessons, quizzes, and assignments. Finally, 86.23% of learners accept that system was very user-friendly and *ease of use*.

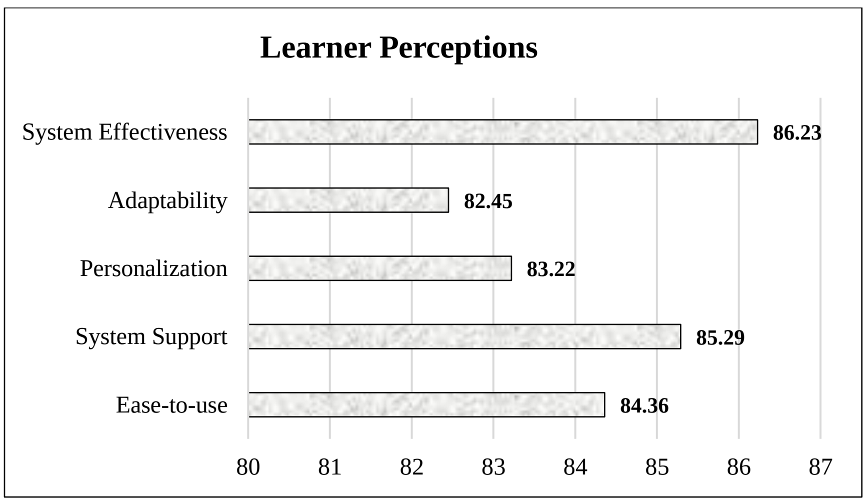

Figure 7.20– Learner's Results of Feedback Questionnaire

7.5.1.2 Adaptability

The capability of the system to synchronize it working and processes, to most closely suit to its learner, supporting him/her through learning pursuit, offering new settings as per needs and preferences, is termed as adaptability/adaptivity. The responses of the learner reactions while using SeisTutor has been presented in Table 7.14. 86.79% of the learners showed that they were comfort with the pedagogy flip, out of which 49.10% of the learners were strongly satisfied and 37.73% of learners were satisfied. Considering the learner performance after the pedagogy flip, 83.40% learners were agreed that they were achieving the learning in terms of high score. Out of which 43.39% learners were strongly satisfied and 39.62% were satisfied. Finally considering more parameters discussed in the Table 7.14, the overall results shows that the learners were adapting the contents offered by the SeisTutor.

Table 7.14– Analysis of responses of Learner Feedback Questionnaire: Adaptability

	Questions	Degree				
		Strongly Satisfied	**Satisfied**	**Neutral**	**Dissatisfied**	**Strongly dissatisfied**
Adaptability	Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor?	23	20	3	4	3
	Were you comfortable with the pedagogy flip by the SeisTutor?	26	20	2	3	2
	Did you feel that your performance improved after pedagogy flip?	23	21	3	2	2
	The pre-learning procedure provided by SeisTutor after pedagogy flip was at the right level that you understood.	23	22	3	3	2
	The tutoring session was at the right level of difficulty for me after changing the tutoring strategy.	19	20	9	2	3
	Were the learning contents as per your learning style after pedagogy flip?	28	18	2	2	3
	Did you think, the test provided to you was at the right difficulty level after pedagogy flip?	24	18	5	3	3
	Did the course provide to you at your educational needs?	21	24	3	2	3
	Did you think that when you reach to the next learning level, you had already known all the previous chapters?	22	25	2	1	3
	Did you have the experience to return back to the previous chapters, if you had any errors or doubts int that?	23	24	2	2	2

7.5.1.3 Personalization

The impact of various algorithms build in modules provided by SeisTutor in terms of their reaction has been analyzed and summarized in Table 7.15. 81.13% of the participants were satisfied with the tutoring strategy provided by the system, which includes 43.39% of the learners were satisfied and 37.73% of the learners strongly satisfied. Additionally, 84.90% of the learners were satisfied with the learning contents provided, out of which 43.39% of the learners were strongly satisfied, and 41.51% of the learners were satisfied as well. Moreover, consider the learning style of learners, 83.46% of learners were not aware of their learning style, and remaining 16.54% of the learners were an idea of the term ‘learning style’ that means very less known about the learning styles. At last, 81.13% of the learners were satisfied with the dynamically generated learner profile with SeisTutor with 50.94% were strongly satisfied, and 30.19%, were satisfied.

Table 6.15 – Analysis of responses of Learner Feedback Questionnaire: Personalization

	Questions	Degree				
		Strongly Satisfied	Satisfied	Neutral	Dissatisfied	Strongly dissatisfied
Personalization	Did SeisTutor satisfy you with learner profile identification in real-time of your learning profile?	27	16	4	3	3
	Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor?	23	20	3	4	3
	The information provided by SeisTutor is at a level that you understand.	23	22	3	3	2
	The tutoring session was at the right level of difficulty for me.	19	20	9	2	3
	As a learner, did you feel that your learning style was appropriately judged?	28	18	2	2	3
	Did you think, the test provided to you was at the right difficulty level?	23	21	3	2	2
	Once, tutoring begins and you were tutored, were your learning preferences sufficiently satisfied?	24	18	5	3	3
	Did the experience of learning by your own learning preference, make you perform better?	21	24	3	2	3

7.5.1.4 System Support

The system support is the assistance provided by the tutoring system during learning process. The results of the learner perceptions have been recorded and shown in Table 7.16. The results of the questionnaire asked to the learner showed that the learner were satisfied and they like to recommend the tutoring through SeisTutor without instructor help. The analyzed results indicates that 83.01% of the learners were agreed that the learning support provided by SeisTutor was at the level of satisfaction out of which 39.62% of the learners were satisfied and 43.39% of the learners were strongly satisfied. Additionally, considering the navigation support provide by the SeisTutor, 77.35% of the learners were satisfied with the system navigation support for enabling easy access to needed information out of which 35.85% were satisfied and 41.51% were strongly satisfied. Moreover, the support provided by the Pre-learning procedure for tutoring initiation, as a total 77.35% of the learners showed an agreement out of which 45.28% of the learners had strong agreement and 32.07% of the learners had agreed that the SeisTutor pre-learning procedure was helpful.

Table 7.16 – Analysis of responses of Learner Feedback Questionnaire: System Support

	Questions	Degree				
		Strongly Satisfied	**Satisfied**	**Neutral**	**Dissatisfied**	**Strongly dissatisfied**
System Support	How are you satisfied with the system support in terms of presenting lessons, revisions, and assignments?	23	21	3	2	3
	Were the system help to find the intended learning lessons or tests?	22	25	2	1	3
	The system navigation support enabled finding the needed information easily.	22	19	5	3	4
	Was the pre-learning procedure available in SeisTutor helpful to you?	24	17	6	3	3
	Were you able to understand the language used to explain the lessons in SeisTutor?	19	23	6	2	3
	Were you able to understand the language used to explain the tests/exercises in SeisTutor?					
	The tutoring was flexible to meet my learning requirements.	20	24	5	2	2

7.5.1.5 Ease-of-use

The overall impact of the support and easy-to-use of the SeisTutor to the learning process is assessed and the learner's perceptions have been recorded. The impact of the interactive graphical user interface, the content organization, and the design features of SeisTutor in the learning process has been evaluated through responses of learners. Table 7.17 presents the degree of responses in terms of Ease-of-use. The learner's responses showed that 79.25% of the learners were agreed, out of which 43.39% were strongly satisfied, and

35.84% were satisfied with the interactive GUI and content organization provided by SeisTutor. Moreover, 81.13% of the learners were satisfied out of which 41.51% were strongly satisfied, and 39.62% were satisfied with the SeisTutor in order to compel and support for completion of quizzes and lessons. Finally, learners were very satisfied with the account setup process of the system, which maintains the learners learning progress, grades, and basic account information.

Table 7.17 – Analysis of responses of Learner Feedback Questionnaire: Ease-of-use

	Questions	Degree				
		Strongly Satisfied	Satisfied	Neutral	Dissatisfied	Strongly dissatisfied
Ease-of-use	Were you able to find the pre-learning procedure you were looking for on our system?	23	21	3	2	3
	Did you find the pre-learning information valuable?	22	19	5	3	4
	How the visually appealing was is our tutoring system application?	24	17	6	3	3
	Were you able to understand the language used to explain the lessons in SeisTutor?	19	23	6	2	3
	How easy to navigate to the SeisTutor to find information?	20	24	5	2	2
	How the pre-tutoring and tutoring session's links were easily available?	22	23	3	2	3
	How satisfied are you with the look and feel (user interface design) of this system?	23	21	5	2	2
	How satisfied are you with the account setup experience of this system?	24	23	3	1	2
	How user-friendly is this system? Give a rating	19	20	6	3	5
	SeisTutor compels and supports me to complete the quizzes and lessons.	21	22	4	4	2
	How satisfied are you with the organization/ customization of contents feature of the system?	19	23	4	4	3

The overall evaluation of SeisTutor is presented, 86.13% of learners agreed that tutoring should begin with the identification of learner profile. The learning style and competency level of the learner should be considered and known before tutoring commences. Most of the learners were not aware about their learning style, and about 83.46% of learners never knew about the concept of learning style. Most of the participants liked the artificial intelligence features such as automatic selection of the tutoring strategies, dynamically assessing the learner performance, and flipping the tutoring strategy. Additional suggestions were received from participants regarding improving the efficiency of SeisTutor.

7.6 SUMMARY

The evaluation of the developed tutoring system ‘christened’ SeisTutor is presented and discussed in this chapter. The learner's evaluation helps to gain insights on the impact of the tutoring system and its contribution to the learning of the subject matter of ‘Seismic Data Interpretation’. The experimental evaluation was conducted over 53 participants tutored through SeisTutor. The phased evaluation comprised pre-tutoring tests, post-tutoring tests and assessments of performance during ongoing tutoring. The learner’s feedback questionnaire has been also used to quantify learner perception about SeisTutor. Finally, the learner assessment findings and analysis of learners’ feedback questionnaire have been presented and discussed. The ANOVA statistical test has been used for statistical analysis that designate the significant difference between the pre-tutoring and post-tutoring tests achievements.

In the following chapter, the conclusion drawn from this work, research contribution along with the future work direction in this field will be discussed

CHAPTER 8: CONCLUSIONS AND FUTURE DIRECTIONS

This chapter summarizes the work conducted in this research. The summary of the contribution of conducted research has been underlined. Subsequently, the conclusions and the future directions in this area based on the conducted research have been described.

8.1 RESEARCH SUMMARY AND CONTRIBUTION

The goal of current research work is to plan and advancement of an adaptive student model to make the framework adaptive. The advancement of an adaptive student model prompts the framework that gives the customized course content and custom-made to the necessities and inclinations of the student. The customized course is once in a while utilized in the mentoring framework because the lack of collaborative support and adaptivity. Therefore, to make the tutoring system adaptable, it is necessary to develop an adaptive learner model. Accordingly, the point of this examination is to concentrate on the student model. In this way, we talk about the appropriate response of the examination question - what are the learner modeling technique and characteristics that could help to provide the adaptivity and personalization in ITS? How to develop an adaptive learner model?

The following highlights the research contribution based on the conducted research work.

The adaptivity has been given dependent on the learning style of students. So as to give the adaptivity, the learning style of the student ought to be known first. Therefore, a novel I^2A^2 learning style model has been utilized. The fuzzy logic approach is used for learner modeling and for identifying the learning style of the learner. A fuzzy rule-based method is implemented for the learner model and its sub-models: First, the learner classification model that classifies the learners based on his/her learning styles and competency levels. A learner classification model helps the system to individualize the learner accordingly and tutoring system generates personalized learning content for the individual learner. Second, the learner adaptation model, it adapts the learner needs and evaluates the performance of learner in order to provide the adaptation. A learner model provides adaptive learning content according to the learner need and preference through his/her learning pursuits offering improved learning gain. This has been evidenced through the implementation of the adaptive learner model into prototype ITS - SeisTutor developed for this purpose.

In order to identifying learning style of learner, a learning style inventory is developed termed as Learning Style Question Pool (LSQP). The underpinnings of those inquiries formulate assessment of learners learning style on the developed system.

8.2 CONCLUSION

In this research, a framework for the domain of Seismic Data Interpretation (SDI) is developed christened 'SeisTutor'. The current research work centered to build up a adaptive ITS framework through the advancement in the learner model. The learner model is created utilizing the fuzzy logic technique that is a soft computing approach of Artificial Intelligence (AI). The sub-components of the learner model: learner characteristics model, learner classification model, and learner adaptation model have been implemented through the fuzzy logic approach.

The proposed SeisTutor offers multiple tutoring strategies based on the learner characteristics i.e. learning styles and learning level. The multiple tutoring strategies were developed using multiple fuzzy inference techniques. A learner model and its submodules: learner characteristic module, learner classification module, and learner adaptation module have been implemented using fuzzy rule-based approach. This approach permits the SeisTutor to adapt to the needs of learner and provide personalize tutoring strategies that improve the performance of the learner. Along with the personalize contents, the learner has provided the quizzes. Each quiz has various hints along with each question that enhance the learning process.

For evaluation of system and determining the contribution to the learning for a domain of Seismic Data Interpretation (SDI). An experimental set-up was conducted that involves 53 learners of different academic background. The evaluation has been carried out into the two phases: First, evaluation of performance of learners, and Second, evaluation of developed prototype - SeisTutor, has been discussed as follow.

First, considering the evaluation of the performance of learners, the pre and post-tutoring test has been conducted before and after tutoring. The learners achieved high scores in the post-tutoring test as compared to the pre-tutoring test for the domain of SDI. The ANOVA statistical test has been applied on pre and post tutoring scores of learners for the computation of learning gain. The computed value of F-ratio of ANOVA test, Fcalc = 327.22 at α=0.05, where α is significant level, while the tabulated value of the F-ratio of ANOVA test, $F\alpha$ = 243.3 (as per F-Table). Here Fcalc > $F\alpha$, hence the null hypothesis H_o is rejected and the alternate hypothesis H_a: $\mu 1 < \mu 2$ is accepted. This indicates that there is a significant difference between pre-tutoring and post-tutoring tests achievement. Hence, we infer that the tutoring is successful and effective with SeisTutor. The mean learning gain has been calculated using the mean score of pre-tutoring and post-tutoring test. The mean learning gain of the participants is 42.26%.

Second, the evaluation of the developed prototype – ‘SeisTutor’ has been carried out and the learner’s perception responses have been recorded. The Learner Feedback Questionnaire (LFQ) formulate assessment of learner’s perception on the developed system. The learner’s perception responses have been divided in the five system performance parameter such as System Effectiveness, Adaptability, Personalization, System Support, and Ease-of-use.

The responses of the LFQ during evaluation of SeisTutor is recorded and percentage scores of each system performance parameter is calculated. Considering the first system performance parameter, *system effectiveness*, 84.36% of learners considered that they improved higher learning gain in terms of scores through tutoring with SeisTutor.

Considering *adaptability* features of the system, 85.29% of the learners agreed that they were adapting the changing learning conditions, and the system was to adopt the learner behavior automatically as per their needs. Moreover, considering *personalization*, 83.22% of the learners were feel comforted with the tutoring strategy provided and agreed to the system provided personalized tutoring strategy. Subsequently, considering *system support*, 82.45% of the learners agreed with the help provide by the system in terms of presenting pre-learning procedure, lessons, quizzes, hints, and assignments. Finally, 86.23% of the learners accept that system was very user-friendly and easy-of-use.

Examination of audits uncovers that learning style exceptionally impacts on learner achievements, learning execution, and student fulfillment level. This examination likewise uncovers the choice and assessment standards of the learning style order calculations. The algorithm using the Fuzzy standard model and Bayesian Network were progressively utilized for the programmed expectations of the learning style of students.

8.3 FUTURE WORK

The findings of the developed system in this thesis can be used for further research and development. In the accompanying sections, conceivable future headings are discussed.

Through the discoveries and conversation of the examinations suggestion and future extension have been advanced. Firstly, there is an opportunity to examine the combination of learning style models in versatile training frameworks/mentoring frameworks. So it is prescribed to investigate blended learning style models for the execution of flexibility in the instructive framework. Despite the fact that the Felder learning style model has been generally utilized, it is fascinating to take note of how other contemporary models, for example, I^2A^2, Kolb, and Honey and Mumford model have been utilized and added to adaptivity, in light of their particular qualities and shortcomings. Also, there is a chance to apply calculations for the recognition of blended learning styles for improving the adaptivity in mentoring frameworks. Furthermore, as a student characteristic, learning style is adequately investigated, other student credits to have the right to be investigated and broke down. Aside from it, the future work coordinated as follow.

- Regarding the initial detection of learning style to initiate tutoring, we proposed the concept of static data modeling and dynamic data modeling. In static data modeling, data is collected over a period of time and use to calculate the learning style of learner. In dynamic modeling, the learner information is collected based on the action performed during the learning process and the learner model is updated automatically. Apart from that, the research can be seen as, to explore the various learning parameters for dynamic data modeling such as behavioral parameter, emotion recognition, cognitive skills, and meta-cognitive skills and so on.

- We can extend the concept of adaptivity in the tutoring system in more detail. It means, there is a need to find out more learning parameters that can support to provide the adaptivity in the tutoring system. Currently, the adaptivity concept is based on predefined learning objects such as learner navigation, learning contents, quizzes, assignments, tests, and self-assessment.

- We can work to implement the concept of domain independence in an intelligent tutoring system.

- We can find more learner characteristics and modeling techniques. We can use the blended learner modeling approach using the cognitive and meta-cognitive skills of the learner.

- The interaction through the user's voice can be implemented for future work. The voice recognition feature can allow the system to improve the efficiency of the system and can improve learner performance.

Appendix A

I^2A^2 Learning Style Question Pool (LSQP)

Q. 1. You and your friend are planning an outstation trip. None of you have been to the place earlier. How would you like to gather information about the place?

1. Requesting live demonstration by someone who visited that place.
2. Using written description of the place.
3. Route map of the place.
4. Listening from friends over telephonic conversation.

Q. 2. Suppose you are ailing from a fatal disease. How would you explain to the doctor?

1. Describe verbally what’s wrong with you
2. Use chart, diagram or show a picture
3. Use written description
4. Use a model to explain what was wrong

Q. 3. You are doing a group study on a topic. You most likely

1. Participate by exchanging your thoughts
2. Be a mute listener and observer
3. Interact using written material
4. Request short movie on that topic

Q.4. You are a learner and wish to get information on a new subject. You would prefer to

1. Use text book or written material
2. Get explained by friend or teacher
3. Use activity or experimental approach
4. Watch videos

Q.5. You are the Chief Executive Officer of a multinational and need to make a presentation on a new project. You prefer presentation to majorly comprise of

1. Charts, pictures, diagrams or maps
2. Short movie
3. Written instructions or manuals
4. Case studies or examples

Q.6. How do you remember any incident in your life?

1. What have you seen
2. What have you listened
3. What have you done
4. What have you read

Q.7. You are going to organize a get-together party for some colleagues at a restaurant. How would you order food?

1. Order most popular dish in that café or order what others are eating.
2. Order something that somebody had spoken to you about.
3. Select from the written description in the food menu or recipe of dish
4. Using pictures of all the dishes

Q.8. When you need directions to an unknown place. You would prefer?

1. A clear and legible map
2. Written directions
3. Being told by someone
4. Need someone that will go with you

Q.9. You are planning to purchase a new motorcycle or car. How would you make your decision regarding the purchase?

1. Go through detailed written description of all features
2. By listening to someone who has experience regarding the said automobile.
3. Using test drive or checking all features
4. Using its looks, orientation, and design

Q.10. If you are presented with current sales data of a product of a multinational company and expected to predict the sales in the next month. You would prefer the data in?

1. charts, tables or graph
2. data represented in textual format
3. verbal description by someone
4. Demonstration of the explanation.

Q. 11. When reading a fiction and trying to analyze. You would prefer?

1. To think about the incidents and develop your own new theme
2. You will listen to the facts behind the story
3. Prefer reading something that teaches new fact
4. Prefer some statute, model or image that inferences the new fact

Q. 12. You have been asked to perform in a cultural event in your college or at workplace. You would prefer?

1. To think on something new and perform it through acting
2. Prepare notes and come up with innovative idea
3. Prepare an activity, record it and play it to the audience
4. Prepare the task through a chart or figure and present

Q. 13. Suppose you have joined a project in a university and are working as part of a group. You would prefer that initially?

1. Someone comes up with a new idea and demonstrates it on a common platform
2. Everyone speaks out their idea
3. All share handout notes, written highlights or instructions
4. Showing model, picture or graph

Q. 14. You are working in a renowned automobile company and your manager has assigned you to create a model or design for a new car. How would you prefer to communicate about that model or design to your manager?

1. Through impressive charts or diagrams that explain all features in detail
2. Create a short video to explain all the functions of each part effectively
3. Prepare speech and play it for the manager to listen
4. Prepare a brief case study in the written forms

Q.15. When you attend a conference or a meeting. How would you remember the key points or the people that you interact with?

1. What was told to you
2. What was explained through demonstration
3. What was seen by you or how people looked like
4. The written description that was made available to you

Q.16. You have joined a school or university, what way of teaching, you would like to be used by the teachers?

1. Focused on experiments, group studies or hands on exercises
2. Written notes, books and reading work
3. Pictures, symbols, mind maps, or videos
4. Listening, talking or group learning

Q.17. When you have to advertise a product of a company. You would prefer

1. Using written description, list, manual or detailed features
2. Interaction with people or explaining features of product
3. Short video, action based charts or diagrams
4. Using a model or prototype of product for demonstration

Q.18. When you are bored and want to be relax. You would prefer.

1. Listening to music, discussion or talking to friends
2. Watching a movie, visuals or mind maps
3. Get engaged in an activity such as dance or drama
4. Read novel, epic, story, case study or biography

Appendix B

Learner Feedback Questionnaire (LFQ)

- Did the SeisTutor meet your expectation?
- What is your overall level of satisfaction with SeisTutor?
- The learning through this tutoring system (SeisTutor) was easy.
- Did you feel that you were achieving learning outcomes?
- Did the tutoring system help you to understand the concepts of SDI?
- I would recommend a course through SeisTutor with no instructor help.
- Would you recommend SeisTutor to individual who needs to take another course?
- Did SeisTutor support you to make your study productive?
- How well does this system deliver on your learning intentions?
- Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor?
- Were you comfortable with the pedagogy flip by the SeisTutor?
- Did you feel that your performance improved after pedagogy flip?
- The pre-learning procedure provided by SeisTutor after pedagogy flip was at the right level that you understood.
- The tutoring session was at the right level of difficulty for me after changing the tutoring strategy.
- Were the learning contents as per your learning style after pedagogy flip?
- Did you think, the test provided to you was at the right difficulty level after pedagogy flip?
- Did the course provide to you at your educational needs?
- Did you think that when you reach to the next learning level, you had already known all the previous chapters?
- Did you have the experience to return back to the previous chapters, if you had any errors or doubts int that?
- Did SeisTutor satisfy you with learner profile identification in real-time of your learning profile?
- Were you convenient and satisfied with the tutoring strategy presented to you by SeisTutor?
- The information provided by SeisTutor is at a level that you understand.
- The tutoring session was at the right level of difficulty for me.
- As a learner, did you feel that your learning style was appropriately judged?
- Did you think, the test provided to you was at the right difficulty level?
- Once, tutoring begins and you were tutored, were your learning preferences sufficiently satisfied?
- Did the experience of learning by your own learning preference, make you perform better?

- How are you satisfied with the system support in terms of presenting lessons, revisions, and assignments?
- Were the system help to find the intended learning lessons or tests?
- The system navigation support enabled finding the needed information easily.
- Was the pre-learning procedure available in SeisTutor helpful to you?
- Were you able to understand the language used to explain the lessons in SeisTutor?
- Were you able to understand the language used to explain the tests/exercises in SeisTutor?
- The tutoring was flexible to meet my learning requirements.
- Were you able to find the pre-learning procedure you were looking for on our system?
- Did you find the pre-learning information valuable?
- How the visually appealing was is our tutoring system application?
- Were you able to understand the language used to explain the lessons in SeisTutor?
- How easy to navigate to the SeisTutor to find information?
- How the pre-tutoring and tutoring session's links were easily available?
- How satisfied are you with the look and feel (user interface design) of this system?
- How satisfied are you with the account setup experience of this system?
- How user-friendly is this system? Give a rating
- SeisTutor compels and supports me to complete the quizzes and lessons.
- How satisfied are you with the organization/ customization of contents feature of the system?
- Were you able to find the pre-learning procedure you were looking for on our system?

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PUBLICATIONS FROM THE THESIS WORK

- **Kumar, A.,** Singh, N., & Ahuja, N. J. (2017). Learning styles based adaptive intelligent tutoring systems: Document analysis of articles published between 2001 and 2016. *International Journal of Cognitive Research in Science, Engineering and Education (IJCRSEE), 5(2), 83-98.*

- **Kumar, A.,** Ahuja, N. J., & Singh, N. (2018). Learner Characteristics based Learning Style Models Classification and its Implications on teaching. *International Journal of Pure and Applied Mathematics (IJPAM),* Vol. 118, No. 20, 2018.

- **Kumar, A.,** and Ahuja, N. J. (2019). Assessment of Learning Style of Learner using I^2A^2 Learning Style Model. *International Journal of Innovative Technology and Exploring Engineering (IJITEE), Vol. 8, No. 6C, 154-159.*

- **Kumar A.,** Ahuja N.J. (2020) An Adaptive Framework of Learner Model Using Learner Characteristics for Intelligent Tutoring Systems. In: Choudhury S., Mishra R., Mishra R., Kumar A. (eds) *Intelligent Communication, Control and Devices. Advances in Intelligent Systems and Computing, vol 989. Springer, Singapore. https://doi.org/10.1007/978-981-13-8618-3_45.*

- Singh, N., **Kumar, A.** & Ahuja, N.J., (2018). Implementation and Evaluation of Personalized Intelligent Tutoring System. *International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-6C, April 2019*

- Ahuja, N. J., Singh, N., & **Kumar, A.** (2018). Development of Knowledge Capsules for Custom-Tailored Dissemination of Knowledge of Seismic Data Interpretation. In *Networking Communication and Data Knowledge Engineering* (pp. 189-196). Springer, Singapore.

- Singh, N., Ahuja, N. J., & **Kumar, A.** (2018). A Novel Architecture for Learner-Centric Curriculum Sequencing in Adaptive Intelligent Tutoring System. Journal of Cases on Information Technology (JCIT), 20(3), 1-20.

- Ahuja, N. J., Singh, N., & **Kumar, A.** (2016). Adaptation to Emotion Cognition Ability of learner for learner-centric tutoring incorporating Pedagogy Recommendation, *International Journal of Control Theory and Applications. Vol- 9, pp- 15-30.*

AMIT KUMAR

Professor and Foreign Faculty(IT), Ningxia, China

Experiencing and enjoying new technologies, with improved skills to work in a challenging environment thus paving way for future opportunities and professional growth along with any institute/university.

Experience (10.5 Years)

2019-07 – Present **Professor and Foreign Faculty**
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2018-08 – 2019-06 **Assistant Professor**
DIT University, Dehradun, Uttarakhand, India.

2017-08 - 2018-08 **Senior Research Fellow (SRF)**
University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, India.
DST Sponsored Project, New Delhi, India

2015-08 - 2017-08 **Junior Research Fellow (JRF)**
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DST Sponsored Project, New Delhi, India

2011-08 - 2015-08 **Assistant Professor**
Uttaranchal University (UU), Dehradun, Uttarakhand, India.

2009-08 - 2010-08 **Lecturer**
Uttaranchal Institute of Technology (UIT), Dehradun, Uttarakhand, India.

Education

2016-01 - present **University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, India.**
Ph.D. in Computer Science & Engineering (Thesis Submitted).
Thesis Title - Learner modeling using learner characteristics for implementation of adaptability and personalization in intelligent tutoring system.
Course Work - 71%

2010-08 - 2012-08 **Graphic Era University, Dehradun, Uttarakhand, India**
M.Tech (Full Time) in Computer Science & Engineering (CSE)
Dissertation Title - Wireless Network Security algorithm with hardware chip implementation.
Grade - 69.50%

2005-08 - 2009-08 **Meerut Institute of Engineering and Technology, Meerut (Affiliated to UPTU Lucknow, UP, India)**
B.Tech (Hons.) in Information Technology (IT)
Grade - 75.04%

2003-08 - 2004-08 **J.L.N.S. Inter College Satheri, Muzaffarnagar (U.P. Board Allahabad, India)**
Intermediate (12^{th}) with PCM Group
Grade - 69.60%

2001-08 - 2002-08 **J.L.N.S. Inter College Satheri, Muzaffarnagar (U.P. Board Allahabad, India)**
High School (10^{th}) with Mathematics and Science Group
Grade - 60%

Personal Info.

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Date of Birth

12-03-1988

Language Known

Hindi, English

Marital Status

Married

Achievements

- UGC NET Qualified held on 30^{th} December 2012.
- Nominated for the Top Feedback among Department of CSE at DIT University in April 2019

Programming Skills

- C and C++
- J2SE and J2EE
- Dot Net Programming
- Python
- Machine Learning using Python

Projects

Sponsored Project [Tenure 3 Years]

2015-08 - 2018-08 **University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, India.**
Project Name - Development of knowledge-based tutoring system for seismic data interpretation using visual and analytical tools integrated with intelligent tutoring
Agency - Department of Science & Technology (DST), New Delhi, India
Principal Investigator (PI) – (Prof). Dr. Neelu J. Ahuja, School of Computer Science (SoCS), UPES, Dehradun, Uttarakhand, India.

Academic Projects

2011-08 – present

- Design and Development of an intelligent tutoring system for the domain of java
- Develop a model for tracking real-time emotions like sad, happy, anger.
- Design a neural network model for the recognition of handwriting
- Develop a model for sentimental analysis with the text using a machine learning approach.
- Simulation of the protocol (Like Aloha protocol Implementation)
- Simulation of routing protocol using the Bellman-Ford and Dijkstra algorithm
- Implementation of FTP (File Transfer Protocol)
- Online voting management system using Java Servlet
- Designing a Hardware Chip for the Wireless Security

Workshops/Expert Lectures/Seminar/FDP Attended

27May-31 May 2019 (05 days) **Deep Learning**
Department of Information Technology, DIT University, Dehradun, Uttarakhand, India

28 Mar-29 Mar 2019 (02 days) **Cyber-Physical System for Digital India and Sustainable Development**
The Institution of Engineers (India), Uttarakhand State Centre & Uttarakhand Technical University, Dehradun association with Uttarakhand Science Education & Research Centre

2 Jan 2019 (One day) **Integration of Best International Pedagogical Practice to Indian Higher Education System**
DIT University, Dehradun, Uttarakhand, India.

27 Dec-31 Dec 2018 (05 days) **Machine Learning and Data Analytics with Python**
DIT University, Dehradun, Uttarakhand, India.
Conducted by Electronics & ICT Academy (E & ICT), IIT Roorkee.
Principal Investigator – Dr. Sanjeev Manhas, Asst. Prof., Centre of Nanotechnology, Department of Electronics and Communication, IIT Roorkee,
Co-Principal Investigator – Dr. Meenakshi Rawat, Asst. Prof., Centre of Nanotechnology, Department of Electronics and Communication, IIT Roorkee,

23 Nov.-2017 (One day) **Implementation of Neural Network Models for Pattern Recognition**
University of Petroleum and Energy Studies (UPES), Dehradun, Uttarakhand, India.

- Bootstrap, HTML, CSS, and Java Script
- SQL Server, MySQL, and Database

Area of Interest

- Automata and Formal Language
- Object oriented programming System
- Operating System
- Advance java programming
- Compiler Design
- Design Analysis and algorithms
- Data Structure, Machine Learning
- Expert System and Neural Network

Author

Books Written - 02

Advance Information System Engineering (AISE)
*Paragon Publication, New Delhi, India(*2009-2010*)*

E- Governance
Ashish Publications, Dehradun, Uttarakhand, India.
*(*2010-2011*)*

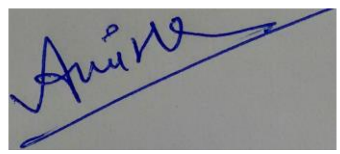
Certificates

- Session chair at International Conference on Advances in Engineering Science Management & Technology (ICAESMT-2019) at Uttaranchal University, Dehradun on 14-15 March 2019.
- Presented research paper in various Springer and Elsevier Scopus indexed conferences across India.
- Contribution as a technical program member in 2nd international conference on intelligent communication, control and devices (ICICCD-2017) at UPES, Dehradun, Uttarakhand, India.
- Contributed as a reviewer in 2nd international conference on intelligent communication, control and devices (ICICCD-2017) at UPES, Dehradun, Uttarakhand, India.

Declaration

I, **AMIT KUMAR** hereby declare that the information given above is true in the best of my knowledge.

Place
Dehradun



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